Smartphones and Biometrics

Gait and Activity Recognition

Mohammad Omar Derawi

Thesis submitted to Gjøvik University College
for the degree of Doctor of Philosophy in Information Security

2012

Smartphones and Biometrics

Faculty of Computer Science and Media Technology
Gjøvik University College

Biometrics and Smartphones - Gait and Activity Recognition / Mohammad Omar Derawi
Doctoral Dissertations at Gjøvik University College 3-2012
ISBN: 978-82-93269-05-2
ISSN: 1893-1227

To my family.

(Mohammad Omar Derawi)

Declaration of Authorship

I, Mohammad Omar Derawi, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Signed:

(Mohammad Omar Derawi)

Date:

Summary

User authentication is a means of identifying the user and verifying that the user is allowed access to services or objects and is a very central step in many applications. People pass through various types of authentication services in their day-to-day activities. For example, to log on to a computer the user is required to know a secret password. Similarly, when turning on a mobile phone the user has to know a PIN code or a touch pattern. Some person authentication methods are based on human physiological or behavioural characteristics, such as fingerprints, face, or voice. Authentication methods differ in their strengths and weaknesses. PIN codes and passwords have to be remembered and gloves have to be removed before fingerprint authentication. Security and usability are essential factors in person authentication. Usability relates to the unobtrusiveness, user-convenience, and human-friendliness of the authentication method. Security is related to the robustness of the authentication method and vulnerability against attacks.

Recent advances in microelectronic chip development allow user authentication based on gait (the way a person walks), using small, light, and low-cost sensors. One of the benefits of this is that unobtrusive person authentication through gait recognition is now possible by using mobile smart phones. Optimization of performance and a strong focus on security, while not ignoring usability, will lead to an increased protection of information on smart mobile devices through the use of gait recognition.

The general aim of the research described in this thesis was to protect smart mobile devices against unauthorized access by using gait recognition based on the data collected from the sensors embedded in these devices. The effort was not only to develop new innovative algorithms to improve performance in gait recognition, but also to develop awareness on the usability of this method by focusing on activity recognition and continuous authentication, as well as assuring security against deliberate attackers.

The main research topics address in this thesis are: (1) Analyzing current techniques employed in accelerometer based gait recognition and identifying usability for deployment in smart mobile devices; (2) Analysis of performance in gait recognition from data collected on inferior sensors employed in smart mobile devices; (3) Recognition of specific gait activities from acceleration data obtained from mobile devices; and (4) Develop a framework for continuous authentication and test its performance.

Research question (1) provides an overview of the state of the art in user recognition based on gait. It covers how experiments are performed, what sensors are used, how data is analyzed, and a comparison of performance results. This overview will serve as the starting point for all further research described in this thesis.

With respect to research question (2), and as far as we know, this is the first Ph.D. dissertation that focuses on gait authentication using accelerometers from mobile devices. A gait-based authentication system has been developed using three different phones, namely the Google G1, the Motorola Milestone, and the Samsung Nexus S. We show how it is possible to use the data from the accelerometer sensors of these phones for gait recognition. We considered different locations on the body to place the mobile phones, in particular the hip and the trousers pocket. We created templates on the phones and compared subsequently collected acceleration data to these templates. We have shown that the data collected on the phones contains sufficient discriminative features to be used for identity verification.

Research question (3) is of the highest importance because we first need to recognize

what kind of activity a user is doing before we can identify the user him- or herself. To have a fully functional gait recognition system implemented in a smart phone, requires activity recognition as a first step. In this thesis we propose and apply a model for automatic gait recognition where we vary the speed of the walking. We applied existing machine learning techniques to the accelerometer data to determine automatically at what speed a person is walking at a given time.

Finally in research question (4), the thesis details how we can use gait recognition in a continuous manner. Generally person authentication is a static access control mechanism, applied when a user needs to access a system. Continuous authentication seeks to address the shortcomings of this approach by continuously re-verifying the identity of the user. This will lead to an increase of security and user friendliness of a gait recognition system on a smart mobile device. In the thesis we have defined a way to implement continuous gait authentication in combination with a way for analyzing performance of such a system.

In addition to the above main contributions of this thesis, we have also investigated different types of related topics. These are either related to gait (video based or using dedicated accelerometer sensors) or to other types of biometrics (fingerprint recognition using a mobile phone camera).

By using dedicated accelerometer sensors, we have been able to investigate the performance of gait in children compared to adults. In addition, we have also investigated the difference in walking of children when their walking deviated from normal walking, e.g. by walking faster or by carrying a book. Furthermore, we have investigated video based gait recognition when using a so-called time-of-flight camera. This is a range imaging camera system that resolves distances based on the known speed of light. To our best knowledge, this was the first time that a time-of-flight camera was using in gait recognition. Similarly there are no known records of gait recognition research using children.

Furthermore have we been researching fingerprint recognition on mobile phones where the images are captured by the embedded camera. The results of the analysis of these images gave a promising performances and lead to new research challenges. A major advantage was that no additional fingerprint sensor was needed as a camera is generally integrated in a mobile phone. Some of the challenges were to detect the fingerprint from the different backgrounds and lighting conditions, in particular when a flash was used. The major challenge was however that now fingerprints are represented as real images instead of binary ones. We noticed that performance depended highly on the embedded camera lens in the selected mobile phones.

A final contribution was building a demonstrator for biometric recognition in a mobile phone that communicated via NFC (Near Field Communication) to an access control mechanism for opening a door. The demonstrator included both gait and fingerprint recognition, as well as a back-up solution using a password.

Acknowledgments

First, I want to express my deepest gratitude my father, Prof. Dr. Omar Derawi and my mother, Fadia Derawi. Thank you both for teaching me the hard work of life and allowing me to realize my own potential. All the support You have provided me over the years was a pleasurable gift teaching me me the value of hard work and education.

I would like to thank my great supervisors, Prof. Dr. Patrick Bours and Prof. Dr. Christoph Busch who gave me the honor to do this Ph.D. for the Norwegian Information Security Labaratory (NISLab) at Gjøvik University College and in a cooperation with the Center for Advanced Security Research Darmstadt (CASED). What makes these places so special is not only the wonderful nature surrounded by mountains and lakes, but also the nice working atmosphere , and the large experience and knowledge gathered there, which all serves as a stable basis for further scientific research. Many thanks to the head and the evaluation committee members Prof. Dr. Stephen Wolthusen, Prof Dr. Simone Fischer-Hübner, Prof. Dr. Raul Sanchez-Reillo and Assoc. Prof. Hanno Langweg. Furthermore, I appreciate the cooperation with Claudia Nickel at CASED and NISLab for the great work we have performed together and thanks to Jayson Mackie for the thesis support. I would also like to thank Werner Blessing and Kathrine Huke Markengbakken for the fruitful conversations.

I am very grateful to all my colleagues, Ali Imran, Anders Lvlie, Bian Yang, Bruno Fernandes, Daniel Hartung, Danish Mairaj, Davrondzhon Gafurov, Erik Hjelms, Fahad Guraya, Faouzi Alaya Cheikh, Gabriele Simone, Gazmend Bajrami, Goitom Weldehawaryat, Hafez Ali Barghouthi, Hai Nguyen, Hans Pedersveen, Heiko Witte, Hewa Balisane, Jean-Baptiste Thomas, Jose J. Gonzalez, Josef Hajek, Knut Wold, Lisa Rajbhandari, Nabeel Al-Bahbooh, Nils Fjelds, Mark Seeger, Marius Pedersen, Martin Olsen, Ondrej Dluhos, Oscar Miguel Hurtado, Pål Erik Endrerud, Ray Chen, Saleh Alaliyat, Sheikh Mahbub Habib, Simon McCallum, Steven Le Moan, Sule Yildirim Yayilgan, Sukalpa Chanda Terje Stafseng, Takashi Watanabe, Waqar Ahmad, Zaid Mastou and friends at the Gjøvik University College and CASED).

A special thanks also to all participants of the four data collections created here at the faculty.

Finally I would like to express my deepest feelings to my dear brothers, my wife and newborn son, for their support and patience.

Contents

1 Introduction **1**
1.1 Research Questions . . . 2
1.2 Ethical Considerations . . . 5
1.3 Structure of the Dissertation . . . 5

2 Background and Related Work **7**
2.1 Authentication . . . 7
2.2 Biometrics . . . 9
2.3 Gait Recognition . . . 17
2.4 Activity Recognition . . . 34
2.5 Mobile Phones and Biometrics . . . 40
2.6 Bibliography . . . 41

3 Contributions and Summary **53**
3.1 Paper contributions . . . 53
3.2 Accomplishments and Future work . . . 57
3.3 Bibliography . . . 59

4 Accelerometer-Based Gait Analysis, A survey **61**
4.1 Introduction . . . 61
4.2 Accelerometer Based Gait Analysis . . . 62
4.3 Discussion and Future Directions . . . 67
4.4 Conclusion . . . 69
4.5 Bibliography . . . 69

5 Towards Continuous Authentication Based on Gait Using Wearable Motion Recording Sensors **73**
5.1 Introduction . . . 73
5.2 Background / State of the art . . . 74
5.3 Evaluation of a Biometic System . . . 83
5.4 Evaluation of a Continous Authentication System . . . 86
5.5 Conclusion and Future Work . . . 88
5.6 Bibliography . . . 89

6 Unobtrusive User-Authentication on Mobile Phones using Biometric Gait Recognition **95**
6.1 Introduction . . . 95
6.2 Gait Recognition . . . 96
6.3 Accelerometer . . . 97
6.4 Definitions . . . 97
6.5 Data collection . . . 98
6.6 Feature Extraction . . . 99
6.7 Results . . . 101
6.8 Conclusion . . . 101

6.9 Future Work . . . 102
6.10 Acknowledgments . . . 103
6.11 Bibliography . . . 103

7 Improved Cycle Detection for Accelerometer Based Gait Authentication 105
7.1 Introduction . . . 105
7.2 Gait Recognition . . . 106
7.3 Data collection . . . 107
7.4 Feature Extraction . . . 108
7.5 Feature Vector Comparison . . . 111
7.6 Results . . . 112
7.7 Conclusion . . . 113
7.8 Future Work . . . 114
7.9 Acknowledgments . . . 114
7.10 Bibliography . . . 114

8 Scenario Test of Accelerometer-Based Biometric Gait Recognition 117
8.1 Introduction . . . 117
8.2 Authentication System . . . 118
8.3 Cycle Extraction Method . . . 119
8.4 Gait Recognition Methods . . . 120
8.5 Scenario Test . . . 121
8.6 Results . . . 122
8.7 Discussion . . . 125
8.8 Conclusion and Future Work . . . 126
8.9 Bibliography . . . 127

9 Towards an Automatic Gait Recognition System using Activity Recognition (Wearable Based) 129
9.1 Introduction . . . 129
9.2 Activity Recognition - Related Work . . . 130
9.3 Scenario and Proposal . . . 136
9.4 Conclusion . . . 139
9.5 Bibliography . . . 139

10 Activity Recognition Using Smart Phones 147
10.1 Introduction . . . 147
10.2 Experiment . . . 148
10.3 Feature Extraction and Analysis . . . 148
10.4 Results . . . 151
10.5 Conclusion . . . 153
10.6 Bibliography . . . 153

11 Gait and Activity Recognition using Commercial Phones 155
11.1 Introduction . . . 155
11.2 Implementation . . . 156
11.3 Experiment . . . 156
11.4 Feature Extraction and Analysis . . . 158
11.5 Results . . . 161
11.6 Conclusions and future work . . . 163
11.7 Acknowledgment . . . 163
11.8 Bibliography . . . 163

A Gait Recognition for Children over a Longer Period 167

A.1 Introduction . . . 167
A.2 Experiment Design . . . 168
A.3 Feature Extraction . . . 170
A.4 Feature Vector Comparison . . . 172
A.5 Analysis and Results . . . 173
A.6 Conclusions . . . 174
A.7 Acknowledgments . . . 175
A.8 Bibliography . . . 175

B Performance of Gait Recognition in Children's Walking Compared to Adults 177
B.1 Introduction . . . 177
B.2 Experiment design and data analysis . . . 178
B.3 Results . . . 181
B.4 Conclusions . . . 182
B.5 Acknowledgments . . . 183
B.6 Bibliography . . . 183

C Gait Recognition in Children under Special Circumstances 187
C.1 Introduction . . . 187
C.2 Experiment design and data analysis . . . 188
C.3 Results . . . 190
C.4 Conclusions . . . 191
C.5 Acknowledgments . . . 192
C.6 Bibliography . . . 192

D Gait Recognition using Time-of-Flight Sensor 195
D.1 Introduction . . . 195
D.2 Experiment Design . . . 196
D.3 Feature Extraction . . . 197
D.4 Analysis and Results . . . 199
D.5 Conclusion . . . 200
D.6 Acknowledgments . . . 200
D.7 Bibliography . . . 200

E Fingerprint Recognition with Embedded Cameras on Mobile Phones 203
E.1 Introduction . . . 203
E.2 Fingerprint Recognition . . . 204
E.3 Data Collection . . . 205
E.4 Evaluation . . . 206
E.5 Discussion . . . 208
E.6 Conclusion . . . 208
E.7 Acknowledgments . . . 209
E.8 Bibliography . . . 209

F Biometric Access Control using Near Field Communication and Smart Phones 211
F.1 Introduction . . . 211
F.2 Related Work . . . 211
F.3 Implementation, Analysis and Evaluation . . . 214
F.4 Conclusion . . . 220
F.5 Acknowledgments . . . 220
F.6 Bibliography . . . 220

G Participant Agreement Declaration 223

H Data Acquisition, Statistics and Methods 225

H.1 Data Acquisition 225
H.2 Statistics 226
H.3 Methods 227
H.4 Bibliography 231

Index **233**

List of Figures

1.1 Relationship between the included papers and the research questions 4
1.2 Relationship between labelled topics and included appendix papers 5

2.1 Architecture of a Biometric System - ISO/IEC JTC1 SC37 SD11 11
2.2 Exemplary ROC curve of a biometric system. [118] 15
2.3 Performance in the algorithm level. 16
2.4 Video Based Approach [91] 17
2.5 Gait collection by floor sensors. a) is a picture of a prototype floor sensor carpet b), shows footsteps recognized, c) shows the time spent at each location in a) and d) shows footstep profiles for heel and toe strikes. Taken and modified from [84]. 19
2.6 Processing flow of method for gait verification 20
2.7 Gait acceleration directions, vertical x, horizontal y, lateral z. The bottom graph, is a combination of x, y and z, defined in Equation 2.3. 23
2.8 Linear interpolation [42] 24
2.9 Moving average filters with and without weights [42] 24
2.10 Top: Time Domain, Bottom: Frequency domain. 25
2.11 Example of one gait cycle [42]. 26
2.12 Cycle length and cycle detection. A subgraph is extracted from the main signal (subgraph) and compared to other parts of the graph. The highest correlations indicate matching positions, and the distance between two samples in two subgraphs constitutes a cycle. The circles represent possible starting locations of the subgraph, and averaging over the distance between these yields the estimate [84] 26
2.13 An actual correct gait cycle. A = start of the step, B = first maximum, C = local minimum, D = last maximum and E = end of the step [84]. 27
2.14 A gait sequence example. Notice extrema that repeats throughout the signal [84]. 28
2.15 After each exact location is known, one can extract the cycles and overlay them on each other [84]. 28
2.16 An averaged gait cycle, showing the mean averaging in red and median averaging in blue [84]. 29
2.17 The histogram similarity method. The gait sample is converted into what represents the enrolled template histogram, while the right gait sample is being verified towards this template [33]. 30
2.18 Gait signal in time (a) and frequency (b) domain [33]. 31
2.19 Level of Activitities [45] 34
2.20 Zero Crossing Rate [74] 38
2.21 The basic of learning process: training and testing [72] 39

4.1 Division of the gait cycle into five stance phase periods and two swing phase periods [22]. 61
4.2 Signal processing flow of method for gait verification/identification. 63
4.3 One gait cycle: begins when one foot touches the ground and ends when that same foot touches the ground again. 65

5.1 Division of the gait cycle into five stance phase periods and two swing phase periods. 74

5.2 Background segmentation for extracting the silhouette picture - subtraction . . . 75
5.3 Gait collection by floor sensors. a) shows footsteps recognized, b) shows the time spent at each location in a), c) shows footstep profiles for heel and toe strikes (x and f(x) indicate the heal/toe locations and footfalls forces, respectively) , and finally d) is a picture of a prototype floor sensor carpet. 76
5.4 Sensor attached at various locations. 76
5.5 Processing flow of method for gait verification. 77
5.6 One gait cycle: begins when one foot touches the ground and ends when that same foot touches the ground again. 79
5.7 Different activities. 82
5.8 A traditional verification process (one-time static). 84
5.9 Continuous Authentication using Gait. 85
5.10 Pyramid Authentication: Continuous authorization and Confidence Level. 89

6.1 Schematic diagram of a piezoresistive accelerometer. 98
6.2 Sample data collected with the G1. The acceleration in x-, y- and z-direction collected during one go is shown, including attaching the phone etc. The dotted lines show the walking part of one go. 99
6.3 Phone attached to subject and the three axes in which acceleration is measured. . 99
6.4 Photograph of the walking setting. 100
6.5 Cycle Detection 101
6.6 DET-curve: Performance of Gait Recognition with an EER of 20.1 %. 102

7.1 Background segmentation for extracting the silhouette picture (subtraction). . . . 106
7.2 Gait collection by floor sensors. a) shows footsteps recognized, b) shows the time spent at each location in a), c) shows footstep profiles for heel and toe strikes, and finally d) is a picture of a prototype floor sensor carpet. 107
7.3 The yellow baseline area indicate the subset with 70 samples that are extracted, the green area is the search area where the baseline is compared against a subset of the search area. The 4 black subgraphs are the baseline at those points it has the lowest distance with the search area subsets, and the difference between them (blue area) indicate the cyclelength 109
7.4 Cycle detection showing how each cycle (i.e the steps) in the resultant vector is automatically detected. 110
7.5 The Neighbour Search is illustrated for the three options that can happen when we are searching for steps, (a) we have jumped too far and since the lowest point in the search area (blue circle) is in the first third we search additional samples back and find the correct minimum point (green). (b) same as with the backward search only that we search forward this time since we have jumped too short. (c) we have jumped satisfactory and the correct minimum is in the middle third of our search area. 111
7.6 The cycles have been extracted by taking each steps starting and ending point. Both these points are minimum points from the resultant-vector data set. 112
7.7 DET-curve: Perfomance of Gait Recognition with an EER of 5.7 %. The x-axis indicates the false acceptance rate (FAR) and y-axis indicitas the false rejection rate (FRR). 113

8.1 Flow diagram of the cycle extraction process. Only during enrolment for the majority voting module the step *Determination of best cycle* is applied. For the CRM module the cycles are normalized in length. 119
8.2 Subjects walked on this route. Authentication was started at the nine numbered points. Dashed lines indicate door sills. 121
8.3 Sample data of section four in which the subjects also had to walk downstairs. . 123
8.4 DET-curves for CRM method using different reference and probe data. 124

8.5 DET-curves for majority voting method using different reference and probe data. 124
8.6 FNMR seperateted by section. 125
8.7 FNMR separated by subject (at a FMR of ca. 10%). 126

9.1 Level of Activitities [25] 130
9.2 The basic of learning process: training and testing [42] 135
9.3 Unsupervised Learning Workflow [1] 136
9.4 Walking and Non-Walking Activities 137
9.5 A full gait signal without segmentation (upper signal figure) and segmented walks (lower signal figure) 138
9.6 Classification of the Activities 139

10.1 A full gait signal without segmentation (upper signal figure) and segmented walks (lower signal figure) 149
10.2 Cycle Detection 150
10.3 The cycles extracted from normal walk 150
10.4 Classification of the Activities 151
10.5 Authentication Process System. Black arrow indicates the process towards template protection. Red arrow indicates activity classification and green arrow the comparison 152

11.1 Left: The main menu of the application, Right: Enrollment and Authentication choice. 157
11.2 Left: Enrollment process, Right: Authentication process 157
11.3 Output of the application (with comparison scores) after an authentication has been performed. The application identifies the activity by marking the text with gray colors. 158
11.4 Cycle Detection 159
11.5 The cycles extracted from normal walk 159
11.6 Classification of the Activities 160

A.1 SENSR GP1 Device 168
A.2 (x,y,z) Acceleration Output 168
A.3 The Sensor Position 169
A.4 Walking Hall 169
A.5 The yellow baseline area indicates the subset with 70 samples that are extracted, the green area is the search area where the baseline is compared against a subset of the search area. The 4 black subgraphs are the baseline at those points that has the lowest distance with the search area subsets, and the difference between them (blue area) indicate the cycle length [8]. 170
A.6 Cycle detection showing how each cycle (i.e the steps) in the resultant vector is automatically detected [8]. 171
A.7 The cycles have been extracted by taking starting and ending point for each step. Both these points are minimum points from the resultant-vector data set. 172

B.1 GP 1 Sensor from Sensr, http://www.sensr.com. 178
B.2 Output example of the GP1 sensor. 179

C.1 GP 1 Sensor from Sensr, http://www.sensr.com. 188
C.2 Output example of the GP1 sensor. 189

D.1 SR-4000 ToF sensor 196
D.2 set-up of the experiment 196
D.3 *(a)*: body parts, *(b)*: ellipse fitting model and *(c)* tracking of legs, blue ellipses for the leg closer to the camera 198

D.4 Illustration of joint locations, (a) 2D stick figure, (b) sample frame and (c) calculated angles. 198
D.5 Extracted data for 5 different walking cycles,(a): original data, (b):filtered data. . 199

E.1 Optical fingerprint sensing by frustrated total internal reflection. 204
E.2 Left: CMOS Sesnor (HTC Desire), Right: CMOS Sensor (Nokia N90) and a cropped/contrasted fingerprint image from each cell, at the same scale factor. . . 205
E.3 Setup for the Nokia N95 capture device. 206
E.4 A traditional verification process. 207

F.1 NFC in the OSI model. 212
F.2 System Architecture of a Near Field Communication System. 213
F.3 A traditional verification process. 215
F.4 Finger position codes according to ISO 19794-2. 216
F.5 Nexus S as a two-factor authentication door key 217
F.6 Information PDU format [13] 218
F.7 NPP packet format as described in version 1 of NPP 219
F.8 NDEF Entry format as described in version 1 of NPP 219
F.9 NDEF Record layout [13] 219

H.1 Left: Google G1, Middle: Motorola Milestone, Right: Samsung Nexus S 225

List of Tables

2.1 Comparison of Various Biometric Features [13] 10
2.2 Biometric performance rates (ISO/IEC 19795-1, 2006) 15
2.3 Database Summary 20
2.4 Data Acquisition Summary 22
2.5 Performances of current wearable sensor-based gait recognitions 33
2.6 Activity recognition research studies. #TP = Test Persons 35
2.7 Studies of activity recognition of daily living (ADL) 35
2.8 Sensors used in different studies. 36
2.9 Supervised learning approaches used for activity recognition 39
2.10 Unupervised learning approaches used for activity recognition 40
2.11 Recognition Accuracies. #TP = Test Persons. L = Laboratory setting, N = Normal circumstance 40

4.1 Experiments Summary. 63
4.2 Data Acquisition Summary. 64
4.3 Examples of Preprocessing Approaches 64
4.4 Experiments Summary. 65
4.5 Time Domain Feature Approaches 65
4.6 Frequency Domain Feature Approaches 66
4.7 Comparison Approaches 66
4.8 Classification Approaches 67
4.9 Performance of current wearable sensor-based gait recognitions. Excerpt of best EER from each author. 67

5.1 Experiments Summary 77
5.2 Data Acquisition Summary 78
5.3 Segmentation Approaches 80
5.4 Time Domain Feature Approaches 80
5.5 Frequency Domain Feature Approaches 80
5.6 Comparison Approaches 81
5.7 Classification Approaches 81
5.8 Performances of current wearable sensor-based gait recognitions 82

6.1 Performance of current wearable sensor-based gait recognition systems. Modified from [7]. 97
6.2 Age and gender distribution of volunteers. 100

7.1 Performance of current wearable sensor-based gait recognition systems. 108
7.2 Comparison of various methods - Equal error rates (EER) are presented 112
7.3 A table showing the main differences between our experiment and others. 113

8.1 Mean times (in milliseconds) needed for cycle extraction and comparison. 122

9.1 Activity recognition research studies. #TP = Test Persons 131
9.2 Studies of activity recognition of daily living (ADL) 132

9.3 Sensors used in different studies. 133
9.4 Feature extraction studies in the time domain 134
9.5 Feature extraction studies in the frequency domain 134
9.6 Supervised learning approaches used for activity recognition 135
9.7 Unupervised learning approaches used for activity recognition 135
9.8 Recognition Accuracies. 137

10.1 Crossvalidation 152

11.1 Crossvalidation 162
11.2 EER when comparison of normal,fast and slow for the same user is considered as a genuine attempt. 162
11.3 EER when comparison of normal,fast and slow for the same user is considered as an impostor attempt. 163
11.4 Performance Evaluation (EER) of Gait Recognition when looking at the comparison of normal,fast and slow separately. 163

A.1 Partial Specification of the GP1 Sensor. 168
A.2 EER Performance results in % on the collected dataset due to age. 173
A.3 EER Performance results in % on the collected dataset due to time. 174
A.4 EER Performance results in % on the collected dataset over time due to gender. . 174

B.1 Partial Specification of the GP1 Sensor. 179
B.2 Age distribution of participants. 179
B.3 EER Performance results in % on the collected dataset. 181
B.4 Performance comparison between adult and children's walking. 182
B.5 EER Performance results in % on the different datasets. 182

C.1 Age distribution of participants. 189
C.2 Performance results on the collected dataset. 191

D.1 EER Performance Results in % on the collected dataset. Second column is first session. Last column is session session 200
D.2 EER Performance Results in % where session 1 as reference template and session 2 as test input (20 users). 200

E.1 Cell phone camera setting for fingerprint image acquisition. 206
E.2 Finger position codes according to ISO 19794-2. 207
E.3 EERs of cell phone fingerprint recognition. Numbers are in percentage. 208

F.1 Cell phone camera setting for fingerprint image acquisition. 215
F.2 EERs of cell phone fingerprint recognition. Numbers are in percentage. 217

H.1 Number of participants and gender information for each dataset. 225
H.2 Number of participants and gender information for each dataset. 226
H.3 Age statistics 226
H.4 Weight statistics 226
H.5 Height statistics 226
H.6 Lenght of leg statistics. 226
H.7 LibSVM parameters in WEKA 229
H.8 MLP parameters in WEKA 229
H.9 RBFNetwork parameters in WEKA 230
H.10 Bayesian network parameters in WEKA 230
H.11 RandomTree parameters in WEKA 230
H.12 LMT parameters in WEKA 230

Chapter 1

Introduction

Businesses and consumers are making increasing use of mobile phones to access corporate data and networks, along with products and services that may demand authentication. As personal mobile devices become more popular the user has come to expect the full range of services from the mobile Internet, as limitations around screen size and interaction capabilities have disappeared.

There are a number of emerging options for biometric authentication via mobile phone. Some examples are fingerprint or face recognition via the camera function, voice recognition via the microphone, gait or activity recognition activity recognition via the accelerometers and/or gyroscopes and gesture recognition via the camera or the accelerometer and gyroscope. The topic of this thesis focuses on two of the mentioned biometric methods, namely gait and activity recognition.

Most of the latest mobile phones have embedded acceleration sensors which can be used for mobile biometric authentication. Gait recognition is a promising option for mobile biometric gait and activity recognition. The term gait recognition describes a biometric method that allows an automatic verification of a person by the way he or she walks. Gait recognition has been based on the use of video sources, floor sensors or dedicated high-grade wearable sensors (mainly accelerometers, although other sensors such as gyroscopes and magnetic field sensors could be used).

The newest of these three approaches is based on wearing motion-recording sensors on the body in different places: on the waist, in pockets, at the ankle and so forth. The main advantage of gait recognition using wearable sensors is that it provides an unobtrusive method of authentication for mobile devices that already contain accelerometers (like mobile phones or tablets). It can be applied for continuous verification of the identity of the user without user intervention. This has a great advantage over other biometric systems such as fingerprint or face recognition, which are also suitable for implementation on mobile phones, but require active user intervention. This advantage of accelerometer based gait recognition compensates for the lesser performance.

As biometric gait recognition only works when the user is walking, this method has to be combined with another authentication method. A suggestion is to add an additional unobtrusive authentication method to mobile phones (for example, voice recognition), which decreases the necessity for regular active authentication and so, increases user friendliness.

Activity recognition can be used as a part of gait recognition. The identification of everyday routine and leisure activities such as walking, running, biking, sitting, climbing and lying down may be tracked by accelerometer sensors in mobile devices. Activity recognition is to recognize a specific activity from the collected accelerometer data, whereas gait recognition is to recognize the person from the collected accelerometer data. Both can be combined to first detect what kind of specific walking (normal, slow, fast, running, etc) a user is doing or if the user is not performing a walking related activity (for example sitting, standing, cycling, or sleeping). Recognition accuracy for activity recognition has shown great results and it could be useful for an automatic gait recognition system.

Biometric gait and activity recognition are also used to prevent malicious users to access stolen phones. Without smartphone security, a subject is exposed to various threats when he/she possesses a phone. The challenges of mobile security is to be aware of data management, identity theft and availability. Attackers are the same as found in the non-mobile computing space, namely the professionals, thieves, black/grey hats. The professionals intend to steal sensitive data and also use the identity to achieve other attacks, whereas thieves want to gain income through data or identities they have stolen. The last mentioned intend to develop viruses, cause damage and also expose vulnerabilities of the device. The security mechanisms in place to counter the threats is divided into multiple categories, as all do not act at the same level. The intention of this thesis is to apply biometric gait authentication to secure un-authorized access when the phone is stolen by professionals or thieves or lost unintentionally.

1.1 Research Questions

Analyzing human gait generated considerable attention for many decades and continues in recent research. Contributions within wearable gait recognition until now have only focused on the task of personal identification where data was retrieved from dedicated external sensors. In this thesis we will be focusing on wearable gait recognition on mobile phones.

The overall goal of this thesis is to investigate the following:

Is it possible, by the use of embedded sensors within personal mobile devices, to perform gait recognition as a security mechanism?

From this goal, we extracted the following main research questions:

1. A state-of-the-art regarding wearable based gait recognition.
2. To develop a gait recognition system on mobile devices and to find out the performance evaluations of it;
3. To develop an activity identification system to detect physical activities from data acquired using mobile device and to perform accuracy evaluations of it;
4. Continuous authentication based on gait using wearable motion recording sensors;

These research questions are answered by the following papers included in the thesis:

1. Mohammad O. Derawi, *Accelerometer-Based Gait Analysis, A survey*. In Norwegian Information Security Conference (Norsk Informasjonsssikkerhetskonferanse, NISK). November 2010.
2. Mohammad O. Derawi, Davrondzhon Gafurov and Patrick Bours. *Towards Continuous Authentication Based on Gait Using Wearable Motion Recording Sensors*. In Continuous Authentication Using Biometrics: Data, Models, and Metrics. IGI Global (ISBN: 9781613501290)
3. Mohammad O. Derawi, Claudia Nickel, Patrick Bours and Christoph Busch. *Unobtrusive User-Authentication on Mobile Phones using Biometric Gait Recognition*. In 6th International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), October 2010. *(Best Paper Award)*
4. Mohammad O. Derawi, Patrick Bours, Kjetil Holien. *Improved Cycle Detection for Accelerometer Based Gait Authentication*. In 6th International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), October 2010.
5. Claudia Nickel, Mohammad O. Derawi, Patrick Bours, and Christoph Busch, *Scenario test of accelerometer-based biometric gait recognition*, In 3rd International Workshop on Security and Communication Networks (IWSCN), May 2011.
6. Mohammad O. Derawi, Gazmend Bajrami, and Patrick Bours, *Gait and Activity Recognition using smart phones*. In 2nd International conference on Pervasive Computing, Signal Processing and Applications (PCSPA), October 2011.
7. Gazmend Bajrami, Mohammad O. Derawi, and Patrick Bours, *Towards an automatic gait recognition system using activity recognition (wearable based)*. In 3rd International Workshop on Security and Communication Networks (IWSCN), May 2011
8. Mohammad O. Derawi and Patrick Bours. *Gait and Activity Recognition using Commercial Phones*. Submitted to journal of Computers & Security - Special Issue on Active Authentication, October 2012.

The relationship between the research questions and the included papers is shown in Figure 1.1.

Even though the main research questions of this thesis focus on gait and activity recognition on mobile devices, we have also analyzed gait recognition on children with regular external accelerometers and video. For the video based gait recognition, we captured the

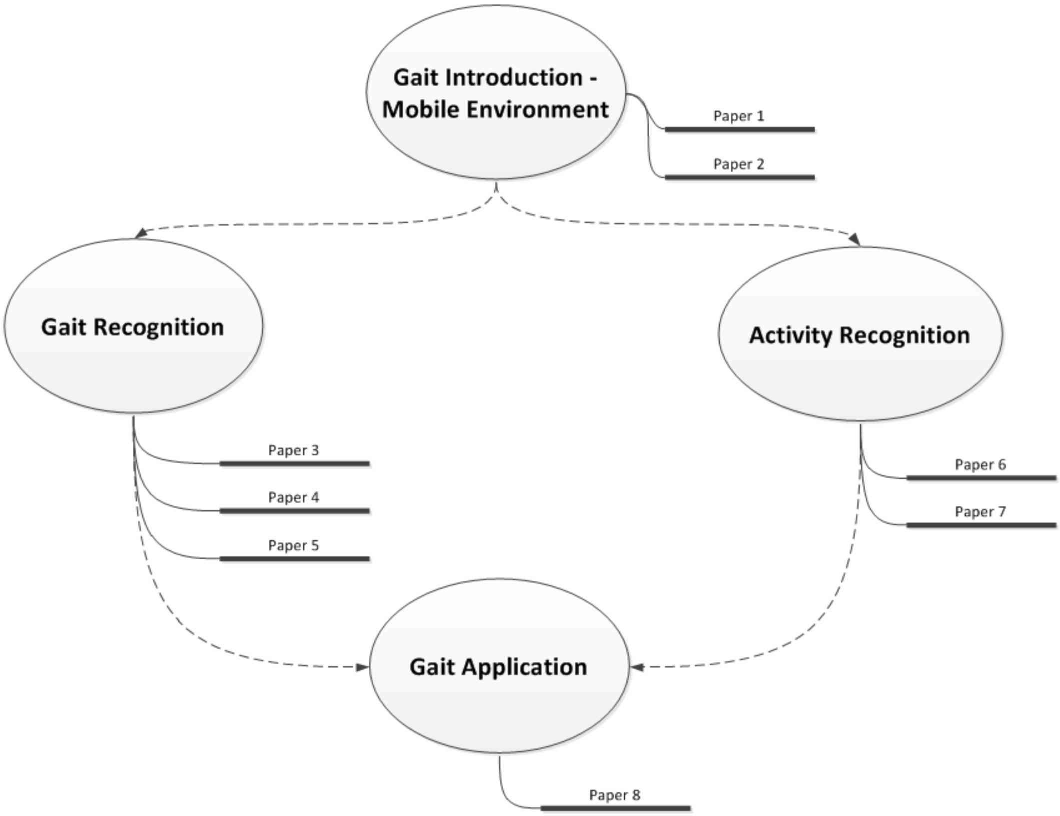


Figure 1.1: Relationship between the included papers and the research questions

walking using an infrared video camera from a certain distance of the subject. Besides gait recognition, but with the focus on mobile device biometrics, we have further been doing research in fingerprint recognition on mobile devices. Finally, we have also investigated on how to develop a secure access control by the use of the newest wireless technology, Near Field Communication (NFC). The papers on these are listed below and can be found in the appendices:

A. Mohammad O. Derawi, Hewa Balisane, Patrick Bours, Waqar Ahmed, and Peter Twigg, *Gait Recognition for Children over a Longer Period*. In BIOSIG 2011, October 2011.

B. Hewa Balisane, Mohammad O. Derawi, Patrick Bours, Waqar Ahmed, and Peter Twigg, *Gait recognition in children under special circumstances*. In 3rd International Workshop on Security and Communication Networks (IWSCN), May 2011.

C. Hewa Balisane, Mohammad O. Derawi, Patrick Bours, Waqar Ahmed, and Peter Twigg, *Performance of Gait Recognition in Childrens Walking Compared to Adults*. In 3rd International Workshop on Security and Communication Networks (IWSCN), May 2011.

D. Mohammad O. Derawi, Hazem Ali and Faouzi Alaya Cheikh , *Gait Recognition using Time-of-Flight Sensor*. In BIOSIG 2011, October 2011.

E. Mohammad O. Derawi, Bian Yang and Christoph Busch, *Fingerprint Recognition with Embedded Cameras on Mobile Phones*. In 3rd International ICST Conference on Security and Privacy in Mobile Information and Communication Systems, MobiSec, May 2011. *(Best Paper Award)*

F. Mohammad O. Derawi, Heiko Witte, Simon McCallum and Patrick bours, *Biometric Access Control using Near Field Communication and Smart Phones*. In 5th IAPR International Conference on Biometrics (ICB12), March 2012.

G. Rubathas Thirumathyam and Mohammad O. Derawi. *Biometric Template Data Protection in Mobile Device Environment Using XML-database*. In 2nd International Workshop on Security and Communication Networks (IWSCN), May 2010.

The relationship between labeled topics and papers included in the appendices is shown in Figure 1.2.

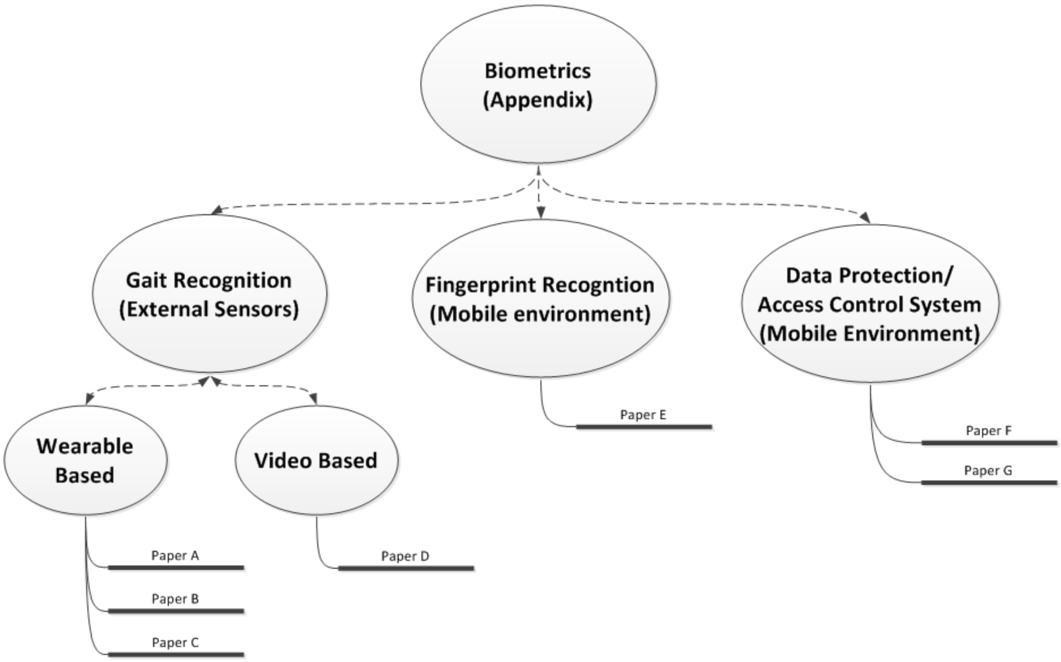


Figure 1.2: Relationship between labelled topics and included appendix papers

1.2 Ethical Considerations

A participant agreement form was signed by the volunteers, which is attached in Appendix G. Data collected during experiments was anonymized such that individuals cannot be identified from the data after the experiment. The link between the experiment volunteer and his/her biometric data exists via a consecutively selected ID number. Such a link needs to exist as long as the experiment takes place. The biometric acceleration data and the personal information of the experiment participants were stored on different media. As soon as the collection of data was finished, the information linking the individual to an ID number was destroyed.

1.3 Structure of the Dissertation

The remainder of the thesis is organized as follows. In Chapter two, an overview of background description and related work on biometrics, is given. In Chapter three, a summary of the contributions of the included papers and thesis is presented. In Chapters four to eleven, the eight research papers listed on page 3 are attached. In the appendices, the six research papers from A-F are presented and the participant agreement form is available.

Chapter 2

Background and Related Work

2.1 Authentication

Authentication is process of determining whether someone or something is who or what it is declared to be [51]. Authentication is an area which has grown in the recent decades and become routinely used in different sectors. Authentication is an important aspect of information security that aims to prevent unauthorized access and to decrease the risk against any theft or disclosure of sensitive information. Examples of authentication are passwords which are used to get access to computers, PIN codes that are used to get access to bank accounts or mobile phones and passports that are used at border control. We identify friends and family by their voices, faces, the way they walk, etc. The words *authentication* and *identification* are terms that are often mixed up by people, but they are different by definition. Authentication is a 1:1 (pronounced one to one) verification of an identity whereas identification means establishing the identity of a person. Identification is also known as a 1:n (pronounced one to n) verification of an identity [13]. As we realize there are several ways in which a user may be authenticated; here we outline the three factors in which authentication can be done:

- Something you *know* (Knowledge based) - For example a secret password, a secret phrase or a PIN code;
- Something you *have* (Object based) - For example a smart card, a token or a physical key etc;
- Something you *are* (Body based) - For example fingerprint, face recognition or gait recognition, in general a biometric property.

2.1.1 Something you know

Something you *know* is an authentication method which is based on some secret the user knows and it is the oldest, best known, and most used way of identifying oneself [13]. Examples of this are passwords and personal identification number (PIN) codes. Today, the most popular and widely used method for authenticating is by entering username and password. It is the most common form to control access to personal computers, networks and Internet. Usage of a PIN code is another example of authentication used to get access to bank accounts and withdrawing money from ATM machine or access to mobile phones.

This authentication method has for a long time been applied because it is cheap, easy to implement and is fast. It is also one of the reasons why it is used in many dissimilar applications which requires the users to apply more than one password/PIN code. Generally it is easier to remember one particular password or a PIN code to be used for many different applications. This raises the issue of stealing or guessing the password. If the user is forced to remember multiple passwords, to change passwords regularly, or to choose to guess difficult passwords, then usually that leads to the risk that the user will write them down. These passwords are often stored in an easy accessible physical place or in a file document. These mentioned drawbacks and difficulties increases the cost of using passwords and PIN codes.

2.1.2 Something you have

When authenticating by something that you *have* requires, the user possesses a token that an authorized user of services has given to ease authentication. Examples of tokens are keys, magnetic cards, SIM cards, smart cards, bank cards, etc. Instead of knowing or remembering longer and difficult passwords, the user can use the token that stores a secret in a secure manner. The only object the user requires for authentication is a piece of hardware containing a unique secret. For an attacker to gain access he must copy or steal the hardware item, which is in most cases very hard. The disadvantage of this authentication method is that costs are higher due to need of hardware (both tokens and readers). In case of loss or theft of a token the user must inform his provider for disabling of the token [13].

2.1.3 Something you are

People might forget passwords and might lose tokens. The authentication method of something you *are*, also known as biometrics, overcomes these problems.

Most biometric features are unique per person and they are found in almost all people in some way or another. Human biometrics can be classified into two types:

Physiological: are the biometric characteristics related to the parts of a human body. Examples are fingerprint, face recognition, DNA, iris and hand recognition.

Behavioral: are the biometrics related to person's behavioral characteristics, such as keystroke recognition, gait recognition, speech/voice recognition and signature recognition, etc.

In Section 2.2 we will give more details on biometrics.

2.1.4 Multi-Factor Authentication

Multi-factor authentication requires the use of elements from two or more categories. Combination of authentication factors may provide greater levels of security to the systems. Some examples are:

Know and Have: An example is a personal PIN (something the users **Know**) and a bank card (something the users **Have**), to get money out of an ATM.

Have and Are: For example a bank card (something the users **Have**) in combination with a signature (something the users **Are**) when getting money at the counter inside a bank.

Know and Are: For example using a combination of PIN code (something the users **Know**) with face recognition (something the users **Are**) to access in a laboratory room.

Are and Are: Combination of multiple biometric modalities, such as using gait (something the user **Are**) and fingerprint (something the user **Are**) in mobile phones for authentication.

When using combination of authentication factors, it is important to make sure that both factors are used and needed for authentication. For example, to have access to a bank account and make a money transfer we need both to know a secret password and have a token, if one of these are missing we cannot make the transfer [13].

2.2 Biometrics

The following is one of the definitions of a biometric system [52].

> Automated recognition of individuals based on their behavioral and biological characteristics.

People have always been able to recognize others by their biometric properties such as voice, face, build and many more. It is not immediately apparent that gait can be used for biometric recognition, however even William Shakespeare referred to gait recognition. In his play, The Tempest [Act 4, Scene 1], Ceres observes *High'st Queen of state, Great Juno comes; I know her by her gait* [111].

According to ISO/IEC JTC 1/SC37 TR 24741 [52], the study of fingerprinting dates back to ancient China; we often remember and identify people by their face or by the sound of their voice; and a signature is the established method of authentication in banking, for legal contracts, and passports.

In 1809 Thomas Bewick, an English wood engraver, started to use his fingerprint as his signature, in combination with his written name to denote identity of his publications [41]. Many researchers contributed with their study on the fingerprints during these years, and in 1846 Nehemiah Grew published the first scientific paper where he described his systematic study on the ridge, valley and pore structure in fingerprints. In the 1880s Faulds, Herschel, and Galton continued the work on fingerprint recognition. Around 1870 Alphonse Bertillon described a system of body measurements for identifying people which was used until the 1920s in the USA to identify prisoners [13]. Features like voice, signature and retina recognition became popular a period after.

In the 1980s, fingerprint scanners, speaker recognition, hand geometry, signature and retina recognition systems were being connected to personal computers to control access to stored information. Based on a concept patented in the 1980s, iris recognition systems became available in the mid-1990s. Today there are many commercially-available systems, utilizing hand and finger geometry, iris and fingerprint patterns, face images, voice, gait, signature dynamics, keystroke dynamics, and hand vein patterns.

2.2.1 Fundamental concepts

There are several biometric characteristics on individuals that can be used for identification or authentication purposes. These biometric characteristics posses features which can be extracted for the purpose of automated recognition of individuals. The most common physical biometric characteristics are the eye, face, fingerprints, hand and voice; while signature, typing rhythm and gait are the most common behavioral biometric characteristics. According to [54], a biometric characteristic should have the following properties:

Universality: Each person should have the characteristics.

Distinctiveness: Any two persons should be sufficiently different in terms of the characteristics.

Permanence: The characteristics should be sufficiently invariant over a period of time.

Collectability: The characteristics can be measured quantitatively.

In order to be able to use a biometric system, these first four properties should be satisfied. For a biometric authentication system to be practical, three more properties should also be considered [54]:

Performance: Measures the recognition accuracy and speed, the resources required to achieve the desired recognition accuracy and speed, as well as the operational and environmental factors that affect the accuracy and speed.

Acceptability: Indicates the extent to which people are willing to accept the use of a particular biometric identifier in their daily lives.

Circumvention: Reflects how easily the system can be fooled using fraudulent methods.

As all these properties are needed, a practical biometric system should have the desired recognition accuracy and speed, be accepted by people and harmless, and should also provide proper security against any possible attack. It is impossible to choose one biometric feature as the best solution for all situations or to say that this feature is better than another. Each biometric feature has its own strengths and weaknesses. To decide which feature to use in a particular situation depends on that situation and the user demands. A way to classify biometrics characteristic is by using the properties described above. In Table 2.1 the classification is done for some biometrics. The values are ranging from high to low (where high is best, except for circumvention where low is the best).

Table 2.1: Comparison of Various Biometric Features [13]

Biometric Features	Univ	Dist	Perm	Coll	Perf	Acce	Circ
DNA	H	H	H	L	H	L	L
Ear	M	M	H	M	M	H	H
Face	H	L	M	H	L	H	H
Facial Thermogram	H	H	L	H	M	H	L
Fingerprint	M	H	H	M	H	M	M
Gait	M	L	L	H	L	H	M
Hand Geometry	M	M	M	H	M	M	M
Hand Vein	M	M	M	M	M	M	L
Iris	H	H	H	M	H	L	L
Keystroke	L	L	L	M	L	M	M
Odor	H	H	H	L	L	M	L
Palmprint	M	H	H	M	H	M	M
Retina	H	H	M	L	H	L	L
Signature	L	L	L	H	L	H	H
Voice	M	L	L	M	L	H	H

2.2.2 Biometric systems

Given the variety of applications and technologies, it might seem difficult to draw any generalizations about biometric systems. All such systems, however, have many elements in common. Biometric samples are acquired from a subject by a sensor. The sensor output can be sent to a processor which extracts the distinctive but repeatable measures of the sample (the features), discarding all other components. The resulting features can be stored in the database as a reference, sometimes called a biometric ”reference” or (in this case) a biometric ”template”. A new sample can be compared to a specific reference, to many references or to all references already in the database to determine if there is a match. A decision regarding the identity claim is made based upon the similarity between the sample features and those of the reference or references compared.

Figure 2.1 illustrates the information flow within a general biometric system, showing a general biometric system consisting of data capture, signal processing, storage, matching and decision subsystems. This diagram illustrates both enrollment, and the operation of verification and identification systems. In the following we describe each of these subsystems briefly. It should be noted that, in any real biometric system, these conceptual components may not exist or may not directly correspond to the physical components.

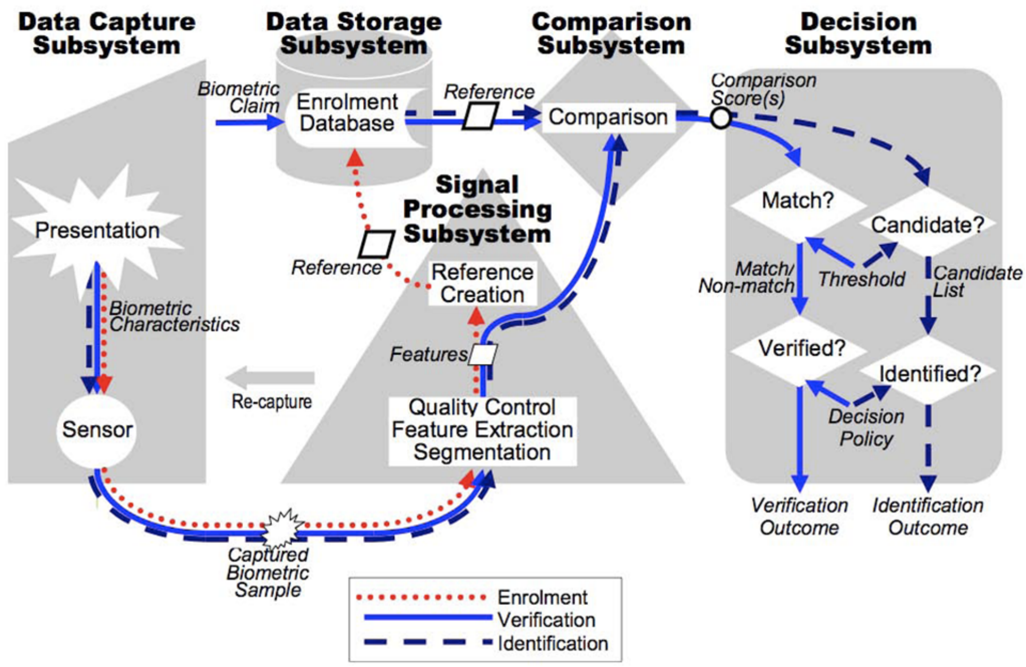


Figure 2.1: Architecture of a Biometric System - ISO/IEC JTC1 SC37 SD11

Data capture subsystem: Biometric systems begin with the collection of a signal from a behavioral/biological characteristic. As data from a biometric sensor can be one- (fingerprint), two- (vein) or multi-dimensional (keyboard dynamics), we are not generally dealing with images. To simplify our vocabulary, we refer to raw signals simply as samples.

Signal processing subsystem: The signal processing subsystem extracts the distinguishing features from a biometric sample. This may involve locating the signal of the subjects biometric characteristics within the received sample (a process known as segmentation), feature extraction, and quality control to ensure that the extracted features are likely to be distinguishing and repeatable. Should quality control reject the received sample/s, control may return to the data capture subsystem to collect a further sample/s.

Data storage subsystem Biometric references are stored within an enrollment database held in the data storage subsystem. Each reference is associated with details of the enrolled subject. It should be noted that prior to being stored in the enrollment database, references may be re-formatted into a standardized biometric data interchange format. References may be stored within a biometric capture device, on a portable medium such as a smart card, locally such as on a personal computer or local server, or in a central database.

Comparison subsystem: In the comparison subsystem, the features are compared against one or more references and comparison scores are passed to the decision subsystem. The scores indicate the degree of fit between the features and reference/s compared. For verification of a claim of enrollment in a simple system, a single specific claim of a subject would lead to the comparison of a submitted sample to a single reference, resulting in a single comparison score between the submitted sample and the claimed reference. For identification of an unknown individual without a claim to a specific reference, many or all references in the database may be compared with the features, resulting in the output of a score for each comparison, or a list of ”candidate” matches from the database.

Decision subsystem: The decision subsystem uses the comparison scores generated from one or more attempts to provide the decision outcome for a verification or identification transaction.

In the case of verification, the features are considered to match a compared reference when the comparison score exceeds a specified threshold. A claim about the subjects enrollment can then be verified on the basis of the decision policy, which may allow or require multiple attempts.

In the case of identification, the enrollee reference is a potential candidate for the subject when the comparison score exceeds a specified threshold, and/or when the comparison score is among the highest k values generated during comparisons across the entire database. The decision policy may allow or require multiple attempts before making an identification decision

We will in the following go into more details within the functions of a general biometric system, i.e. the enrollment and recognition phase:

Enrollment In enrollment, a transaction by a subject is processed by the system in order to generate and store an enrollment record for that individual. The enrollment record will consist of the biometric reference (a stored sample, template or model) for the individual and perhaps other information, such as a name. At the time of enrollment, the veracity of this other information must be ascertained from external source documentation, such as birth certificates, passports or other trusted documents. The use of biometrics does not obviate the need for care in ascertaining the validity of these documents at the time of enrollment. Note that in some identification systems enrollment may not be a distinct phase; an encounter with an individual who is not found in the database results in an enrollment.

Verification (or authentication) In verification, a transaction by a subject is processed by the system in order to verify a positive specific claim about the subjects enrollment (e.g. I am enrolled as subject X). Verification will either accept or reject the claim. The verification decision outcome is considered to be erroneous if either a false claim is accepted (false accept) or a true claim is rejected (false reject). It should be noted that that some biometric systems will allow a single person to enroll more than one instance of a biometric characteristic (for example, an iris system may allow a person to enroll both iris images, while a fingerprint system may support the enrollment of two or more fingers as backup, in case one finger gets damaged). Verification is also referred to as (1:1) - one to one - comparison.

Identification In identification, a transaction by a subject is processed by the system in order to find the identifier of the subjects enrollment record. Identification provides a candidate list of enrollment records. This list may be empty or may contain only one record. The identification process is considered successful when the subject is enrolled, and at least one enrollment record is in the candidate list. The identification is considered to be erroneous if either an enrolled subjects enrollment record is not in the resulting candidate list (false-negative identification error), or if a transaction by a non-enrolled subject produces a non-empty candidate list (false positive identification error). Identification is also referred to as (1:n) - one to many - comparison.

2.2.3 Basic System Errors

Biometric authentication systems typically require specifications in terms of maximum allowable degree of errors, usually expressed as error rates. It is important to understand the type of the errors before a solution is designed. Some of these errors can be directly related to the results deduced from a pattern recognition application, which is inherently similar to a biometric authentication system. What is certain is that any biometric authentication system will make false decisions, and that the true value of the various error rates cannot be computed or theoretically established; it is only possible to obtain statistical estimates of the errors using test databases of biometric samples.

In this section the intuitive and theoretical meaning of different error types (found in ISO/IEC 19795-1) will be introduced. The main focus will be on the errors made by the comparison engine of a verification system. As described earlier the comparison engine of an authentication system corresponds to the biometric comparator that makes a (1:1) comparison decision based on a score s as illustrated under the decision subsystem in Figure 2.1. The comparison engine of an identification system makes (1:n) comparison decisions.

2.2.3.1 Comparison

A comparator is a system that takes two samples of biometric data as input and returns a comparison score that indicates their similarity as output. This score is used for determining whether the two biometric samples are from the same source or not. In order to deepen the meaning of a comparator, the following notations are introduced:

b **and** b': Two biometric characteristics sources (e.g., two fingers or two faces).

$B = f(b)$ and $B' = f(b')$: The associated machine representations of these biometrics. f represents the process of sampling the data with a sensor and, perhaps, applying some processing to extract the features B and B'.

Unfortunately, the biometrics sources b and b' (of the actual subjects) are functions of time (meaning that a biometric characteristic, e.g. a fingerprint, may change over time), and the sensing function f could also perhaps be a function depending on environmental factors such like temperature or humidity. Therefore, this variability must be introduced and is indicated by the denoted t in the following

$$B = B(t) = f(b(t)) \text{ and } B' = B'(t0) = f(b'(t'))$$

Biometric comparator makes measures whether or not the samples are from the same source. This measure is typically an algorithmically defined similarity measure, which is highly dependent on the precision of the acquisition device and machine representation of the biometric samples, such as using a distance metric. If the similarity measure is able to capture nuances in biometrics that differentiate one person from the next, this similarity should then successfully relate to the comparison probability. Nevertheless, the comparison engine takes b and b' as input and computes a score:

$$s(B',B) = s(B'(t'),B(t)) = s(f(b'(t')), f(b(t)))$$

Typically one of the machine representations (for instance B) is the enrolled sample, which is rarely changed unless desired for specific reasons, and the other of the machine representations (for instance B') is the live query sample. However, this score $s(B',B)$ only expresses some sort of likelihood that the true biometrics b' and b are the same. It can be assumed that for a higher similarity comparison score $s(B',B)$, the more likely that two biometrics come from the same b. An alternative way to compute comparison scores is to determine distances , or dissimilarities, $d(B',B)$ between the samples B' and B. Such distance scores score are calculated by the use of a distance metric, e.g. the Absolute distance between corresponding points in two sets. The distance metric should in principal give a small intra-class distance, meaning that samples from the same person get a low score, and a large inter-class distance, meaning that samples from different persons should give a high score. The assumption is then the opposite of a similarity comparison score, namely that a lower distance comparison score would result that the more likely two biometrics come from the same b.

The biometric comparison engine determines the accuracy of the error rates in terms of the trueness of two hypotheses. Given two biometric samples, we construct the null hypothesis and the alternate hypothesis as follows:

$$H_0 \Rightarrow \textit{the two samples match}; \tag{2.1}$$

$$H_a \Rightarrow \textit{the two samples do not match}; \tag{2.2}$$

2.2.3.2 Accuracy

The definition of accuracy in biometric applications can differ; as well as the decision making of that biometric application, which therefore gives different definitions of errors. There are many terminologies that express the accuracy of an application, such as False Match Rate (FMR), False Accept Rate (FAR), False Positive Rate (FPR), etc. The most common type of errors used are False Match Rate (FMR), False Accept Rate (FAR), False Non Match Rate (FNMR), False Rejection Rate (FRR) and the Equal Error Rate (EER).

FAR and FRR are terminologies that reflects the accuracy at system level, whereas FMR and FNMR reflect the accuracy at algorithm level. The difference between the two pairs of error terminologies is that FAR against FRR (and/or FMR against FNMR) consider the Failure to Acquire rate (FTA).

The common and standardized metrics for measuring the accuracy of biometric recognition algorithms are given in Table 2.2.

The trade-off between FMR/FAR and FNMR/FRR can be shown by using the Decision Error Trade-off (DET) or Receiver Operating Characteristic (ROC) curves. The difference between the DET and ROC curve is the change in the y-axis, where (1-FNMR) is substituted instead of FNMR for the DET-curve.

FMR and FNMR are typically traded off against each other, usually to increase either security or convenience/inclusiveness. Both are functions of a threshold value, which can be raised to a system-dependent level to make the biometric system more secure by reducing the number of false matches. However, at the same time the number of false non-matches increases and more valid users are rejected. The other way around, more impostors may gain access, if the threshold value is chosen at a lower level to make the application more convenient to users. This trade-off between security and convenience, FNMR and FMR, is illustrated in the curve in Figure 2.2, and the requirements of different types of applications (forensic, civilian and high security) are positioned.

High-security applications may require a very high threshold value, to keep the risk of granting access to impostors as low as possible. The operator might even accept a higher rate of valid users being rejected, only to be sure no access is granted to invalid users. Forensic applications, such as the identification of an individual from a huge population rather apply a lower threshold to avoid that the sought-after is wrongly excluded from the matches. In this case, the forensic examiner might accept to manually inspect a greater number of incorrect matches. The threshold used in civilian applications is found somewhere in the middle, depending on the application, closer to security or comfort.

The last stage is to decide what threshold the system should use. This depends highly on the application. The extreme cases for the thresholds are when FMR is close to 1 and FNMR is close to 0, or vice versa. The first extreme case implies that you are nearly always able to authenticate yourself, but so does everyone else, and not only are they able to authenticate them as themselves, but also as anyone else. Another way to interpret this is that you will have full convenience, but no security at all. The other extreme case implies

Table 2.2: Biometric performance rates (ISO/IEC 19795-1, 2006)

Performance Metric	**Acronym**	**Description**
Failure to capture rate	FTC	The proportion of biometric capture process that failed to produce a captured biometric sample
Failure to extract rate	FTX	The proportion of successfully captured samples that failed to generate templates
Failure to acquire rate	FTA	The proportion of a specified set of acquisitions that were failures to accept for subsequent comparison the output of a data capture process. This can be two cases: fails to capture or fails to generate templates from successfully captured samples. By function: $FTA = FTC + (1 - FTC) * FTX$
Failure to enroll rate	FTE	Proportion of biometric enrollment transactions (that did not fail for non-biometric reasons), that failed to create and store a biometric enrollment data record for an eligible biometric capture subject, in accordance with a biometric enrollment policy
False match rate	FMR	The proportion of the completed biometric non-match comparison trials that result in a false match. FMR reflects the accuracy in algorithm level.
False non-match rate	FNMR	The proportion of the completed biometric match comparison trials that result in a false non-match FMR reflects the accuracy in algorithm level.
False accept(ance) rate	FAR	The proportion of the completed biometric non-accepted comparison trials that result in a false accept(ance). FAR reflects the accuracy in system level. By function: $FAR = FMR * (1 - FTA)$
False reject(ion) rate	FRR	The proportion of the completed biometric accept(ance) comparison trials that result in a false non-accepted case. FRR reflects the accuracy in system level. By function: $FRR = FNMR * (1 - FTA) + FTA$
Genuine accept rate	GAR	GAR = 1 - FRR
Equal error rate	EER	Point where FAR equals FRR (or FMR meets FNMR)

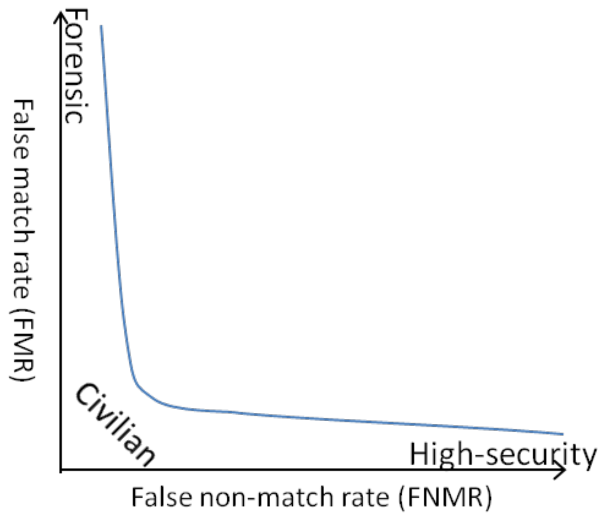


Figure 2.2: Exemplary ROC curve of a biometric system. [118]

that you can never authenticate you as yourself, but this also accounts for everyone else, so they can never authenticate as you either. Therefore you will have high security, but no convenience.

The Equal Error Rate (EER) is a point where FMR=FNMR and can be found by intersecting DET curve with the dashed red line (function where $x = y$ in Figure 2.3). This threshold gives this joint error rate, which is very commonly used to compare different systems against each other, and thus, it generally gives one an idea of how well the system has performed.

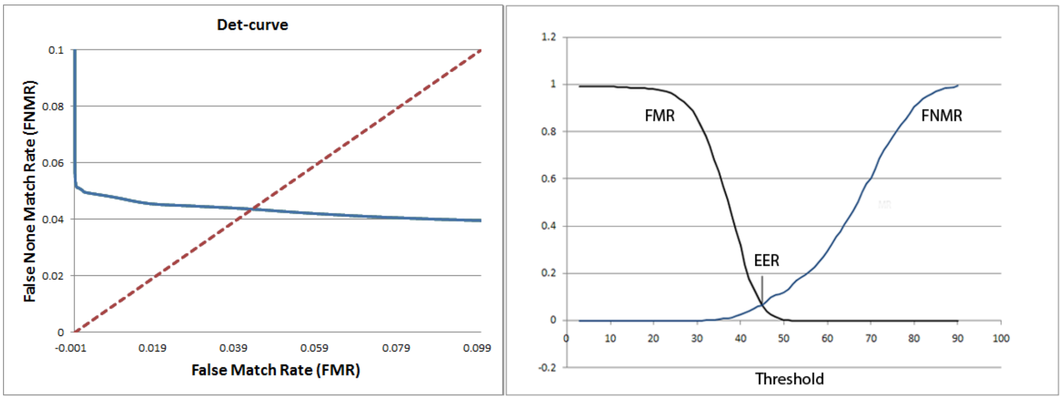


Figure 2.3: Performance in the algorithm level.

Biometric applications may be categorized into three main groups [118]:

1. **Forensics application**, where biometric is used mainly for the *identification* and where no pre-enrollment exist, for example criminal investigation for corpse identification, parenthood determination, etc.

2. **Government applications**, where biometric is used mainly for the *authentication* of personal documents, such as passports, ID cards and driver's licenses; border and immigration control; social security and welfare-disbursement; voter registration and control during elections; e-Government.

3. **Commercial applications**, where biometric is used mainly for the *authentication* of physical access control; network logins; e-Commerce; ATMs; credit cards; device access to computers, mobile phones, PDAs; facial recognition software; e-Health.

This order generally reflects the emergence and use over time of biometric recognition systems. Initially found mainly in the field of criminology and forensics, biometrics underwent a market breakthrough when governments started to integrate biometric access control mechanisms in personal documents. While access control and authentication have remained the primary purpose, other fields of application are taking off. Google's photo organizer software Picasa and social-networking site Facebook have integrated face recognition algorithms to make it easier to search and display all photos featuring a certain person. Picasa is available as an application for several operating systems, while its photo sharing web site (Picasa Web Albums) and Facebook provide face recognition online. Biometric systems embedded in cars of a vehicle fleet can help to identify the driver, adjust seat, rear mirrors, and steering wheel to meet individual preferences.

Commercial and government applications are likely to overlap in some fields. Future e-commerce, e-health and e-government services may require authentication with the help of biometric personal documents issued by governments, as soon as they are used by a large enough part of the population. Some developing countries have used biometrics for voter registration in the run-up to elections in order to avoid out-dated voter lists and election fraud.

Market forecasts on biometric spending are generally optimistic. Growth is expected especially in commercial and government applications, where the biometrics industry and the related smart card chip industry benefit from government decisions toward the adoption of electronic personal documents and biometrics.

2.3 Gait Recognition

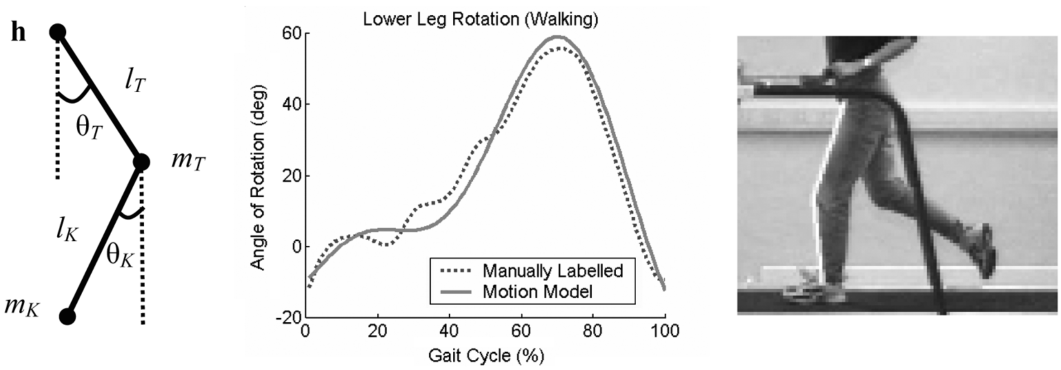
Data for gait recognition is generally captured using 3 different types of equipment:

- Video cameras;
- Sensors installed in the floor; and
- Wearable sensors attached to the body of the user.

The main focus of this thesis is mostly on wearable sensors, for both static and continuous authentication. This section also discusses the best possible body locations where motion-recording sensors (MRS) could be attached or worn. Some examples are also provided regarding the performance accuracies of such locations. The three approaches in gait recognition were first proposed by Ikeda et al. [50] and later revised by Gafurov [33] are (1) Video Sensor Based (VS); (2) Floor Sensor based (FS) and (3) Wearable Sensor based (WS). In the following we will go into more details of each of these approaches.

2.3.1 Video Sensor (VS) Based

VS is the most widely used gait recognition technique, as it allows the collection of gait features from a distance. The system of video sensor approach would typically consist of one or several digital or analog cameras (black-and-white or color), with suitable optics in order to acquire the necessary gait data. It is mainly used in surveillance and forensics applications [43, 67, 35]. With the use of video processing techniques there could be several possible ways in identifying a person. The techniques could be thresholding to convert the images into black and white, background segmentation which performs a simple background subtraction or pixel counting to count the number of light or dark pixels. Figure 2.4 shows an example of the VS-based approach how to extract information from an video image.



(a) basic model (b) variation in knee angle (c) image analysis

Figure 2.4: Video Based Approach [91]

Alternative techniques are to extract static features like stride length which are determined by body geometry and dynamic features from body silhouettes [11]. The VS based gait analysis techniques can be classified as model-based [122, 12] and model free [93]. The main advantage of model based approaches is the direct extraction of gait signatures from model parameters, but it is computationally expensive. Model free techniques characterize the body motion independently from body structure. VS gait analysis can also be categorized according to the technology used, as marker-based or marker-less. In marker based systems specific points in the subject's body are labeled by markers. By tracking these points in the video sequence the body motion can be tracked and analyzed [25, 60]. VS based gait recognition provides wide range of gait features and many works utilized different sets of features and classification techniques. Benabdelkader et. al. [8] used stride length and cadence as features extracted.

During the last decade when scientists have been analyzing the gait movements of criminals caught on CCTV in order to compare them with those of a suspect [117]. In December 2004, there was a case where a perpetrator robbed a bank in Denmark[66]. Two surveillance cameras were recording the robbery. One camera placed at the entrance that recorded the robber's frontal view (process of walking in, standing and walking in the bank during the robbery, and leaving the bank). The other camera placed inside the bank that recorded the cashier's desk, provided the persecution enough evidence to convince the court rely on the gait-analysis tool to convict the perpetrator of the robbery. At about the same time in late December 2004, there was a murder crime scene in the United Kingdom. A podiatrist explained the supreme court that the person captured on the video and some other previous videos of the murderer was the same [17]. An other case occurred around mid-April 2008, when a burglar was caught because of his bow-legged walk [7]. Despite the fact that the burglars face was unable to be seen, they could identify the burglar. Even though in most cases during the robbery, the perpetrator wears a mask to hide his body characteristics of identity such as face and hands so no evidence like face or fingerprints could be shown or found, cameras are still available and useful in recording the gait where enough information can be used in the process of perpetrator identification.

2.3.2 Floor Sensor Based

The floor sensor approach, considers spreading touch sensors or pressure sensors on the floor (on a mat), where the positions of people are accurately detected. Gait data can be measured while people walk across in two different ways. The first is a force to the ground by the person's walk, which is also known as the GRF (Ground Reaction Force). The other is to measure the pressure, i.e the force over an area applied by a subject in a direction perpendicular to the surface. Floor sensors have several studies proposed to recognize human behavior using floor sensors [97, 85]

In a research from the University of Southampton [82], a floor sensor for gait recognition was prototyped as illustrated in Figure 2.5. Commercial customizable low profile floor mat system that captures multiple sequential footsteps for analysis of foot function and gait are even available for purchase. They also provide data for objective and quantified analysis that is used to answer clinical and biometrics related questions.

2.3.3 Wearable-Sensor Based

The third gait approach, a part from the video sensor (VS) based and floor sensor (FS) based gait recognition approach, is the wearable sensor (WS) based approach. By definition, in this approach a recording sensor worn or attached to the human body, for example in the pockets, waist or shoes. These sensors can measure numerous types of data. Gyro sensors (measure rotation), accelerometers (measures acceleration), telemetry sensor system (measures footfall timing) [63], have so far had a great focus in gait research, where especially accelerometers were used most for gait recognition. These accelerometers are becoming an

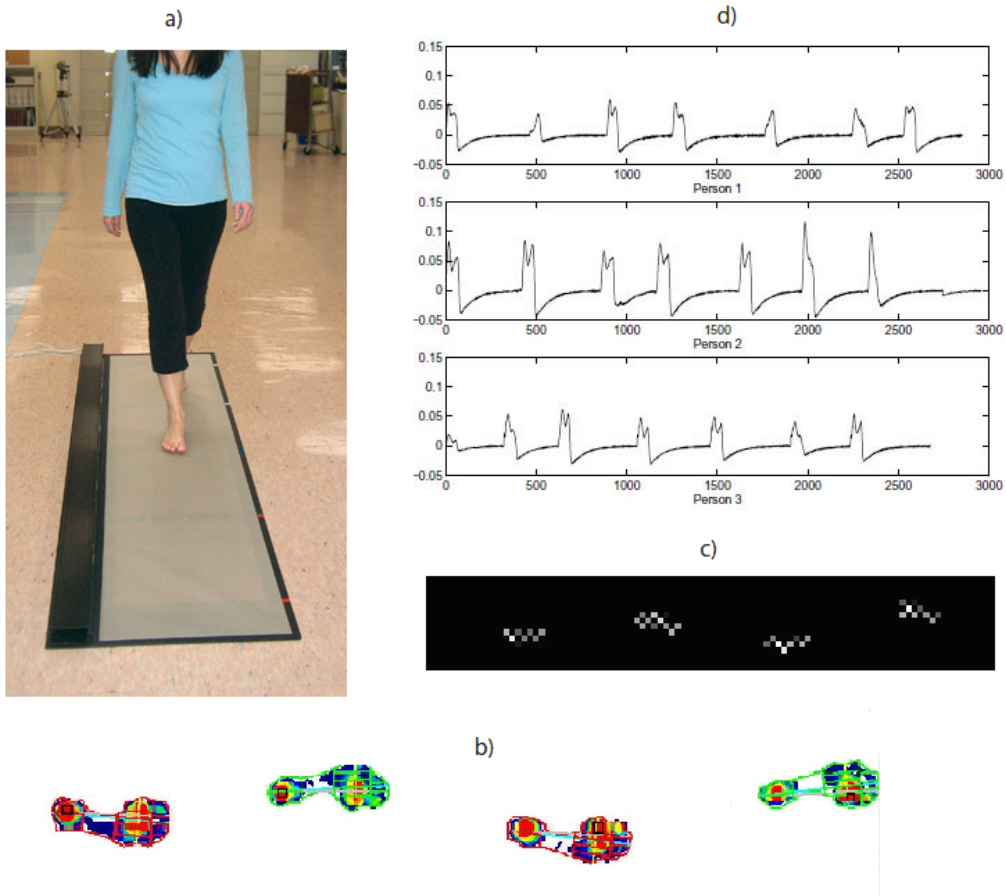


Figure 2.5: Gait collection by floor sensors. a) is a picture of a prototype floor sensor carpet b), shows footsteps recognized, c) shows the time spent at each location in a) and d) shows footstep profiles for heel and toe strikes. Taken and modified from [84].

important tool into our daily life. All of the new mobile smartphones nowadays, are already equipped with wearable-sensors; they use built-in accelerometers in order to detect when the device rotates, so it can tell whether to display what is on the screen in portrait or landscape format. Moreover, these devices can be used for detecting when a person lifts the phone to the ear so that phone calls are answered automatically.

It has increased the interests in performing research on different aspects within wearable-based gait biometrics. Analyzing of the gait data is a challenge-full task for creating efficient feature extraction approaches that works properly for both activity and gait recognition. For general WS-based gait analysis, the signal processing flow is illustrated in Figure 2.6.

One of the more challenging research topics today lies within continuous authentication. While the user is walking, the motion is recorded by the acceleration sensor in a way that recording could be used to verify the identity of the user continuously. In static authentication, the authentication mechanism will make a decision about the correctness of the claimed user identity directly after the person has walked. This decision is either accepting or rejecting this person, resulting in either access or not to the particular system. In continuous authentication, the user is by default accepted since his or her identity has been verified by a static authentication mechanism. A biometric continuous authentication mechanism will therefore only reject users if they have proven not to be the genuine user. In order to be able to measure the genuineness of the user, then trust levels and a way to

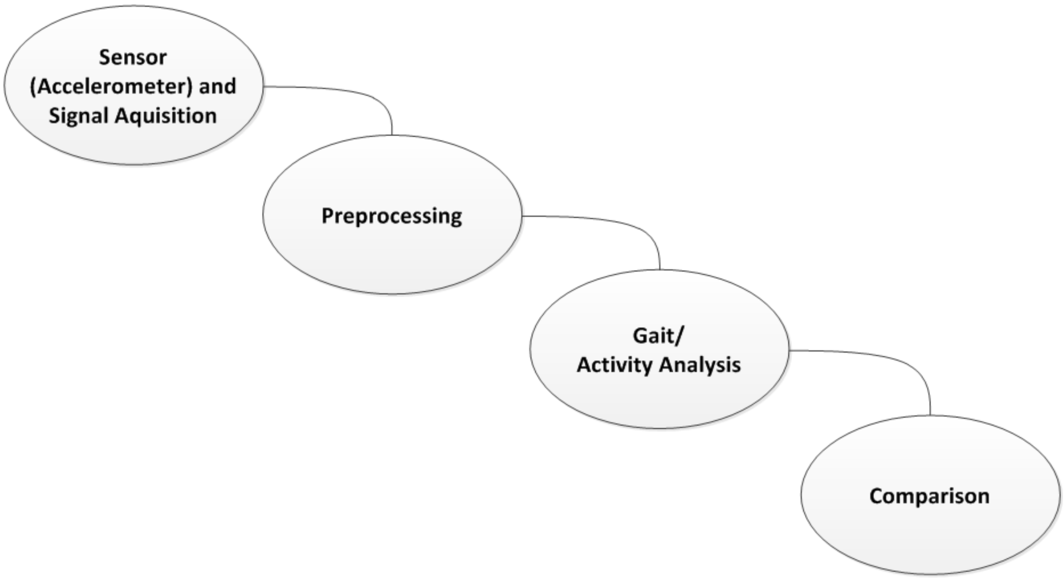


Figure 2.6: Processing flow of method for gait verification

adjust the trust level based on newly defined penalty and reward functions is needed.

2.3.3.1 Databases

There are no publications so far that introduce an official public database created for accelerometer based gait recognition. However, there is one semi-public gait data-set which was collected at McGill University in June and July, 2010 by Frank et al [32]. Researchers have the ability to test their algorithms on it but will not be able to obtain a copy of the database. This data-set contains the raw sensor data collected from a mobile phone (HTC Nexus One) in the pocket of 20 individuals, performing two separate 15 minute walks on two different days. The subject information, including the gender, height, weight, and descriptions of clothing and shoes warn on each day are also available.

The rest of the databases that have been created are considered as private databases. In Table 2.3 a summary of collected databases performed in research is given. The table includes the activity tested and the number of subjects.

Study	Walking activities	Subjects	Year
Mantyjarvi et al. [78]	normal	36	2001
Henriksen et al. [40]	normal	20	2004
Ailisto et al. [2]	normal	36	2005
Buvarp [16]	normal	22	2006
Gafurov [33]	normal	21, 30, 50, 100	2005 - 2008
Rong et al. [106]	normal	35	2007
Holien [42]	normal, fast, slow, circle	60	2008
Mjaaland [84]	normal (mimicking)	50	2009
Derawi et al. [28]	normal	51	2010
Wang et al. [125]	normal	25	2010
Frank et al. [31]	normal,running, lingering	24	2010
Nickel et al. [90]	normal	36	2011

Table 2.3: Database Summary

The databases are all controlled experiments. A controlled experiment is a fixed laboratory setting which means it is quite different from a real world scenario due to its importance in getting as much data as possible during the research. While in everyday life people keep their mobile phone in their pockets or hold it in their hands, the phone continuously moves in different directions, it rotates and we usually attach it to a single part of the body during the whole time. As shown in the table 2.3 the number of volunteers differs quite a lot. The number of test-subjects has been different from one research to another which makes the recognition performances incomparable with eachother. Clothing may appear to be another issue because gait is different from one person to another and clothing may turn out to be a critical parameter in affecting the gait recognition research outcomes. Moreover, only a few studies have made research in different behavioral settings and one study has shown that there is a slight change of the gait-signal of a person from one day to another [42].

2.3.3.2 Data acquisition

There are several types of equipment available to gain the accelerometer data: a dedicated accelerometer, GPS device, mobile phone, etc. these accelerometers measure the acceleration of three directions, first vertical or x-direction, second horizontal or y-direction and third lateral or z-direction. Acceleration is quantified in the SI unit meters per second per second (m/s^2), in the unit Gal (defined as 1 centimeter per second squared (1 cm/s^2)), or popularly in terms of g-force (g). An accelerometer output value is a scalar corresponding to the magnitude of the acceleration vector. The most common acceleration, and one that we are constantly exposed to, is the acceleration that is a result of the earth's gravitational pull. This is a common reference value from which all other accelerations are measured (known as g, which is around 9.8m/s^2).

Depending on where the accelerometers are built (into cell phones or dedicated devices) they normally output values at different sample-rates per time unit. In commercial devices, piezoelectric, piezoresistive and capacitive components are commonly used to convert the mechanical motion into an electrical signal. Piezoelectric accelerometers rely on piezoceramics (e.g. lead zirconate titanate) or single crystals (e.g. quartz, tourmaline). They are unmatched in terms of their upper frequency range, low packaged weight and high temperature range. Capacitive accelerometers typically use a silicon micro-machined sensing element. Their performance is superior in the low frequency range and achieve high stability and linearity.

Modern accelerometers are often small micro electro-mechanical systems (MEMS), and are indeed the simplest MEMS devices possible, consisting of little more than a cantilever beam with a proof mass (also known as seismic mass).

A typical accelerometer has the following basic specifications [109].

Analog vs. digital: The most important specification of an accelerometer for a given application is its type of output. Analog accelerometers output a constant variable voltage depending on the amount of acceleration applied. Digital accelerometers output a variable frequency square wave, a method known as pulse-width modulation.

Number of axes: Accelerometers are available that measure in one, two, or three dimensions. The most familiar type of accelerometer measures across two axes. However, three-axis accelerometers are increasingly common and inexpensive (especially in smartphones).

Output range: To measure the acceleration of gravity for use as a tilt sensor, an output range of 1.5 g is sufficient.

Sensitivity: An indicator of the amount of change in output signal for a given change in acceleration. A sensitive accelerometer will be more accurate.

Sampling rate: The sampling rate of a sensor is usually measured in Hertz and indicates the limit of the near-unity frequency response of the sensor, or how often a reliable reading can be taken. Humans cannot create body motion much beyond the range of 10-12 Hz. For this reason, a bandwidth of 40-60 Hz is adequate for tilt or human motion sensing. For vibration measurement or accurate reading of impact forces, bandwidth should be in the range of hundreds of Hertz.

Other specifications include: Zero g offset (voltage output at 0 g), noise (sensor minimum resolution), temperature range, bias drift with temperature (effect of temperature on voltage output at 0 g) sensitivity drift with temperature (effect of temperature on voltage output per g) and power consumption.

Several studies have been using different accelerometer sensors for data capturing. An overview of the placement of sensors and their models used in the literature is given in Table 2.4.

Study	Placement	Sensor
Sazonov et al. [107]	shoe	MEMS accelerometer
Iso and Yamazaki [53]	breast/hip	cell phone accelerometer
Mostayed et al. [87]	whole body weight	force plate
Gafurov [33]	ankle/pocket/arm/hip	3D accelerometer (MRS)
Rong et al. [105, 106]	waist	3D accelerometer (analog)
Annadhorai et al. [3]	leg	wireless accelerometer(Tmote Sky)
Hynes et al. [48]	pockets	phone headset
Lee and Lee [68]	waist	3D accelerometer (ADXL05, analog)
Ailisto et al. [1, 2]	waist	3D accelerometer (ADXL202JQ, analog)
Frank et al. [31]	hip	cell phone accelerometer
Derawi et al. [28]	hip	cell phone accelerometer
Sebastijan and Damjan [112]	hip	cell phone accelerometer
Baechlin et al. [4]	ankle	3D accelerometer
Henriksen et al. [40]	elastic belt on body	3D accelerometer
Holien [42]	hip	3D accelerometer (MRS)

Table 2.4: Data Acquisition Summary

The wearable sensors uses accelerometers to collect acceleration data in the x, y and z direction, but there are many ways to go from here. Figure 2.7 shows acceleration graphs for different directions. Each of the three top graphs are fragments of gait acceleration, while the bottom graph is a combined version, or the resultant.

Gafurov et al. [33] refers to many different methods of combining the signals, but states that the best performance is achieved when using all three dimensions combined into a resultant vector :

$$r_t = \sqrt{x_t^2 + y_t^2 + z_t^2}, t = 1, ..., N, \tag{2.3}$$

where r_t, x_t, y_t and z_t are the magnitudes of resulting, vertical, horizontal and lateral acceleration at time t, respectively and N is the number of recorded observations in the signal.

2.3.3.3 Pre-processing

Pre-processing is the first step performed with the gait signal in all three directions (x,y and z). Several gait pre-processing methods have been used in literature. Some studies do include pre-processing and others not. The measured acceleration signals are sometimes

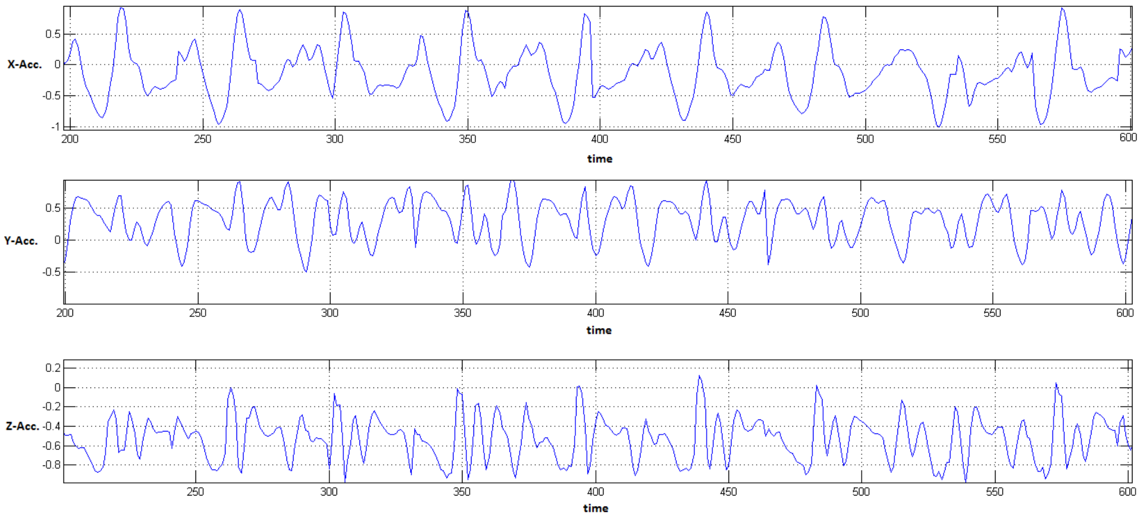


Figure 2.7: Gait acceleration directions, vertical x, horizontal y, lateral z. The bottom graph, is a combination of x, y and z, defined in Equation 2.3.

outputted as low-frequency signals. These signals are easily affected by different environmental noise of the experiment like the equipment's electronic noise the high frequency noise, etc.

Interpolation:

The sampling frequency of every accelerometer sensor is different and the time is not equal from one outputted sample to another. To make the time constant in the time axis from one sample to the other we must apply a mathematical operation. Usually the raw data shows that the time values obtained are typically very close to the desired values, so a simple linear interpolation operation can solve the problem of unequal time intervals.

If the two known points are given by the coordinates (x_0, y_0) and (x_1, y_1), the linear interpolant is the straight line between these points. For a value x in the interval (x_0, y_1) , the value y along the straight line is given from the equation 2.4

$$\frac{y - y_0}{x - x_0} = \frac{y_1 - y_0}{x_1 - x_0} \tag{2.4}$$

which can be derived geometrically from the Figure 2.8.

Solving this equation for y, which is the unknown value at x, gives Equation 2.5:

$$y = y_0 + (x - x_0)\frac{y_1 - y_0}{x_1 - x_0} \tag{2.5}$$

Noise reduction:

Noise reduction is the process of removing noise from a signal. Noise can be random or white noise with no coherence, or coherent noise introduced by the accelerometer sensor or processing algorithms. The acceleration data contains unwanted values due to several potential noise factors. This is a problem for biometrics in general, and one of the reasons why a perfect reference template does not exist for most biometrics.There are different ways of removing noise from a signal. Holien considered two possible filters in [42],

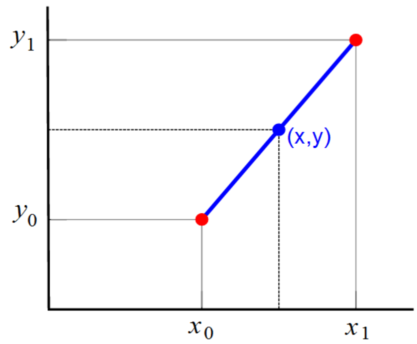


Figure 2.8: Linear interpolation [42]

namely the Moving Average (MA) and the Weighted Moving Average (WMA). These concepts are shown in Figure 2.9 a and b, respectively. The (Weighted) Moving Average filters

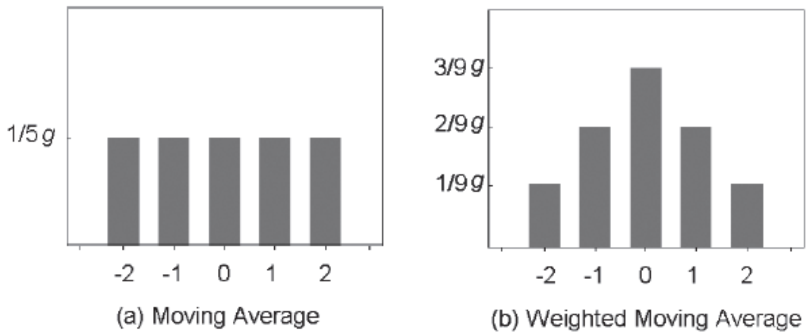


Figure 2.9: Moving average filters with and without weights [42]

rely on values neighboring the value in question. That is, if an extreme value lies in between several average values, the former value will be drawn towards the average to an extent determined by the filters characteristics. The Weighted Moving Average filters let the closest neighbors count the most, with a variable window size, while the non-weighted Moving Average filters do not. The formulas for MA and WMA with a sliding window of size 5 is given in Equation 2.6 and 2.7.

$$MA(a_t) = \frac{a_{t-2} + a_{t-1} + a_t + a_{t+1} + a_{t+2}}{5}, \tag{2.6}$$

where a_t is the acceleration-value in position t. All the four closest neighbors are given the same weight.

$$WMA(a_t) = \frac{(a_{t-2} \cdot 1) + (a_{t-1} \cdot 2) + (a_t \cdot 3) + (a_{t+1} \cdot 2) + (a_{t+2} \cdot 1)}{9}, \tag{2.7}$$

where a_t is the acceleration-value in position t. The current value we are located at are given weight 3, the two closest neighbors weight 2 and the next two neighbors weight 1.

There are also other options than can be used, we can use different window sizes. In [87] Daubechies wavelet was used to remove noise.

2.3.3.4 Data Analysis

User identification from gait patterns with accelerometers used is based on the assumption of the gait acceleration profile being unique at some extent for each individual. First, it is important to compute the feature template vector (that represents the characteristics of the person's gait) to authenticate and of course to store it. The feature vector is again computed during the authentication process, based on a new biometric input and compared to the feature template. An effective analyze of the accelerometer data can be made in two domains; time-domain and/or the frequency-domain as illustrated in Figure 2.10. The aim of the time-domain is analyzing the three acceleration signals (x,y,z) and monitoring how these three signals change over time (t), whereas the aim of the frequency domain analysis is showing how each band of frequencies is given. A given function or signal can be converted between the domains of time and frequency domain by using mathematical operators known as transformation.

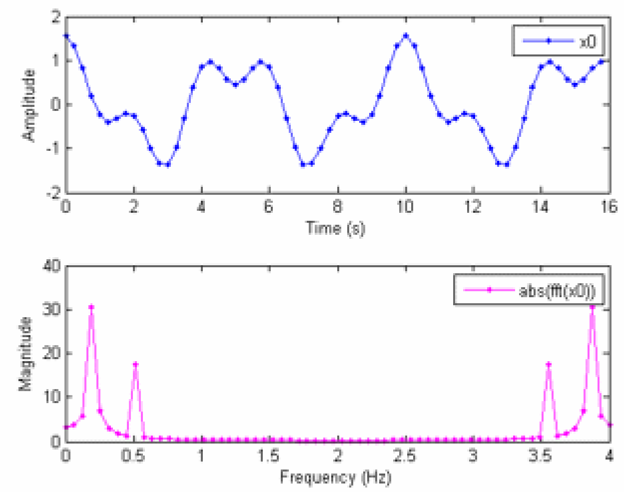


Figure 2.10: Top: Time Domain, Bottom: Frequency domain.

Segmentation

The process of identifying boundaries in gait signals is known as gait segmentation. It can be performed in different ways and is a very important issue. The signals gained from different individuals are a composition of periodic segments recognized as gait cycles and they correspond physically to two alternative steps of the individuals. These cycles begin as soon as the foot touches the ground and finishes when the same foot touches the ground for the second time, this process is shown in Figure 2.11.

The most common used gait segmentation is the cycle detection method as explained by Derawi [26], Gafurov [33], Holien [42] or Mjaaland [84]. The segmentation process starts by estimating how long one cycle is. This is done by extracting a small subset which is further shifted to the overall signal, also known as the autocorrelation. The output of the autocorrelation method is a new signal/curve with peaks. Each peak defines the gait signals starting and ending point. From the first peak to the other the first length of the cycle is estimated. This is repeated until all lengst are estimated, then we are able to estimate the overall cycle length by using the average of all lengths. Mantyjarvi et al. [78] applied more or less same methodology with small differences.

In the following we will in more details describe how the segmentation is performed. Individuals will differ according to the length of their legs, their weight and walking speed. So prior to any cycle detection, it is most practical to perform an automatic estimation of

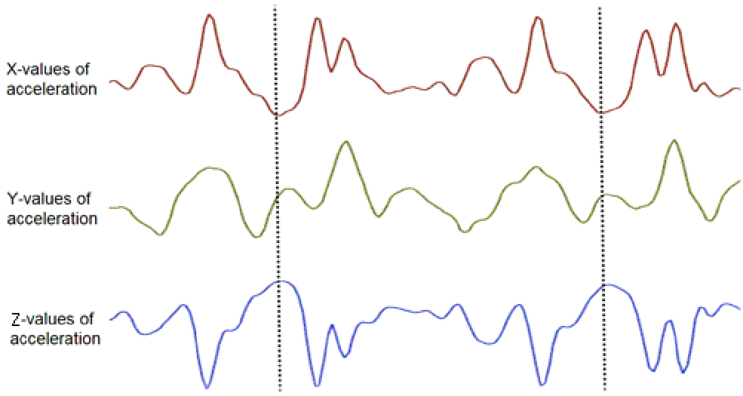


Figure 2.11: Example of one gait cycle [42].

the cycle length. In order to detect cycles, is it very sensible to obtain an estimation of the average cycle length.

The approach is to extract a subgraph from the middle of the gait sequence which is compared to other parts of the graph as illustrated in Figure 2.12

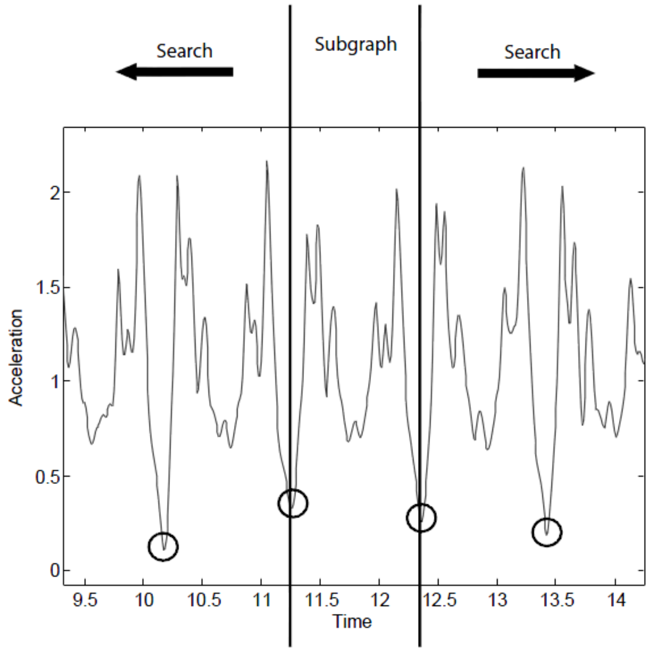


Figure 2.12: Cycle length and cycle detection. A subgraph is extracted from the main signal (subgraph) and compared to other parts of the graph. The highest correlations indicate matching positions, and the distance between two samples in two subgraphs constitutes a cycle. The circles represent possible starting locations of the subgraph, and averaging over the distance between these yields the estimate [84]

.

By calculating the correlation between the subg-raph and other parts of the graph, and remembering the positions with the best match, we can average over the distance between each of these positions. If the starting point of the sub-graph is in the middle, then the correlations are high around that area before and after. If the starting point of the subgraph is either in the beginning or the ending, we might choose a wrong subgraph that is not related to walking data. In this case we might have difficulties in estimating the correct cycle length.

The actual cycle of a person could be defined differently. The beginning of a cycle could be defined freely, meaning that you can choose where in the walking as one wants. Most like a cycle starts when one of the foots is lifted, and ends when that foot is back in the same position. This cycle is represented by Figure 2.13. The easiest way would be to look at characteristics in common of the gait cycles, regardless of person.

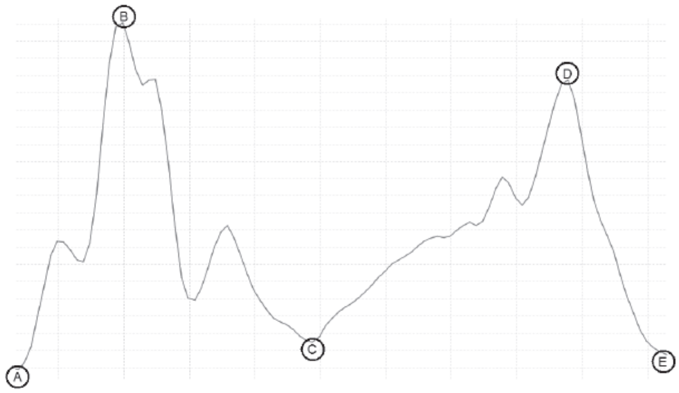


Figure 2.13: An actual correct gait cycle. A = start of the step, B = first maximum, C = local minimum, D = last maximum and E = end of the step [84].

Looking at the gait example in Figure 2.14, the reader might observe many characteristics of the repetitive pattern. Hence, several studies did not concentrate on what is referred to as the actual cycle, but rather any cycle defined between two repetitive points. As the figure shows, the local extrema are clearly visible. In Derawi [26], Gafurov [33], Holien [42] and Mjaalands [84] research, the minima are used for gait cycle detection. The process will be described in the following.

Let N be the estimated cycle length and L the length of the entire gait sequence.

1. The minimum point, defined M, within the middle section of the gait sequence is detected, and used as starting point. This minimum defines the start of a cycle, and will be used as a base point to find others.

2. A search is made forward in the gait signal by jumping N data-points ahead, and scanning the new point for another minimum, with a buffer of 10% samples of the cycle length in each direction. This is repeated until the end of sequence is reached. The minima are stored.

3. A search is made backward from the point M in the gait signal by jumping N data-points backwards, and scanning the new point for another minimum, with a buffer of 10% samples of the cyclelength in each direction. This is repeated until the start of sequence is reached. The minima are stored.

4. The resulting cycle vector is produced, containing the sample locations of all the discovered minima. The distance between these points are the cycles used. Hence, it is known where the exact location of each cycle is.

When each is known, one can extract the cycles as illustrated in Figure 2.15

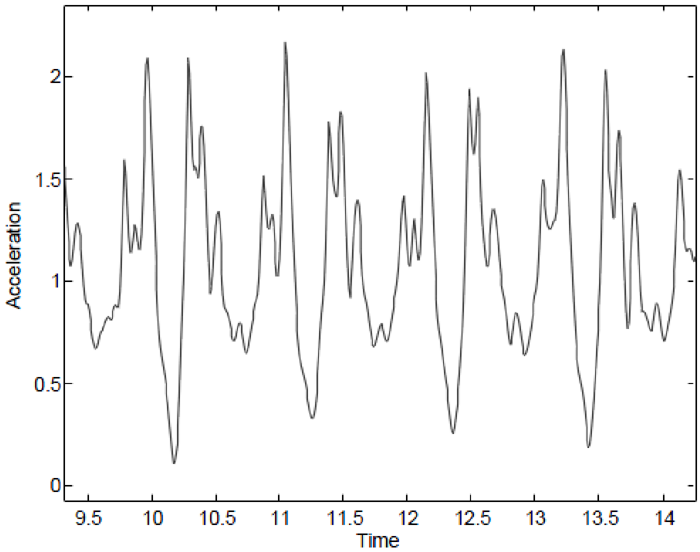


Figure 2.14: A gait sequence example. Notice extrema that repeats throughout the signal [84].

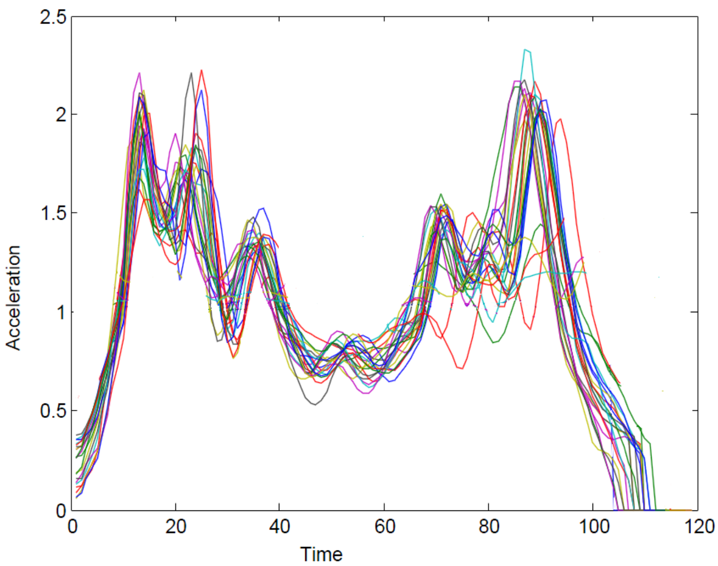


Figure 2.15: After each exact location is known, one can extract the cycles and overlay them on each other [84].

Mantyjarvi et al. [78] and Ailisto et al. [1] performed the approach in almost similar way. Instead of extracting cycles consisting of two steps, then a cycle consisted of only one step. These steps were further normalized into equal lengths.

Feature extraction in the time domain

One of the first applied methods in gait biometrics was the cycle detection which is a continuation of the average cycle method explained earlier. This has been the most applied methods so far. It is a simple approach which obtains the average of all extracted cycles. Despite the frequent use of average cycle method other extraction approaches such as n-bin histograms and cumulants of different orders have been developed as well.

One of the first who applied the average cycle method was Ailisto [1] and Mantyjarvi et al. [78] who averaged all segmentations (steps) in all three signals x, y, and z separately. The averaged signals formed the feature vector for one subject (representation of a user). Gafurov et al. [33] changed the concept slightly. Instead of using all three directions separately, the resultant vector was used. Furthermore, all cycles were averaged instead of the single steps. The averaging that was applied was by calculating the mean or the median. In other papers by Derawi et al. [26] and Gafurov et al. [34] all the extracted cycles were stored used and no average cycle was created.

The choice of averaging tool is a different story because performance is prone to degradation from outliers and normalization. To solve this, proper pre-processing and a wise choice of averaging and normalization tools are necessary. The average cycle is thus computed where all cycles are averaged with each other using different approaches, for example the mean of media as illustrated in Figure 2.16.

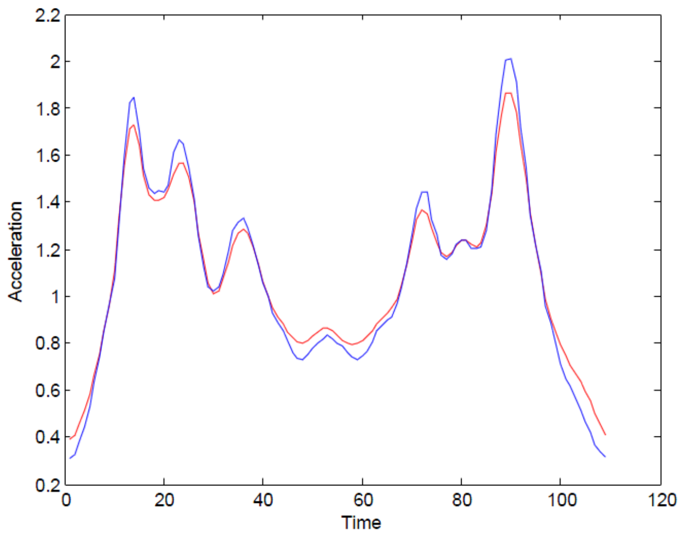


Figure 2.16: An averaged gait cycle, showing the mean averaging in red and median averaging in blue [84].

Another approach by Gafurov [33] and Mantyjarvi et al. [78] used *n-bin normalized histogram* as the feature vector. In a more general mathematical sense, a histogram is a mapping that counts the number of observations that fall into various disjoint categories (known as bins), whereas the graph of a histogram is merely one way to represent a histogram. In general, there is no ”best” number of bins, and different bin sizes can reveal different features of the data.

In the histogram similarity method, n bins of values are computed to form a histogram of the combined gait signal. The histogram is normalized by the number of recorded samples, and a distance metric is used to compute the separability between two such histograms. Figure 2.17 illustrates the process of comparing two histograms.

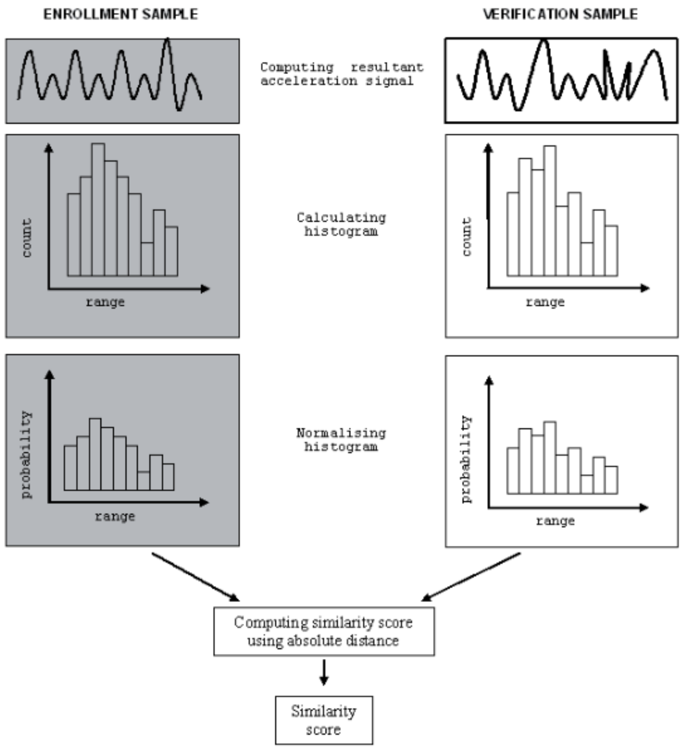


Figure 2.17: The histogram similarity method. The gait sample is converted into what represents the enrolled template histogram, while the right gait sample is being verified towards this template [33].

A third approach (Sprager et al. [112]) experimented with cumulants of different orders. All cumulant coefficients were calculated from zero-lag cumulant to cumulant with a fixed lag constant (for second, third and fourth order) for each gait cycle. Their feature vector was represented by the cumulant coefficients.

Gait feature extraction in the frequency domain

The extraction of the features in the frequency domain differs slightly from the time domain, as mathematical transformations, need to be applied. Among the most efficient ones is known to be the Fourier transform. It is a mathematical operation which makes a transformation of the signal from the time domain to the frequency domain, and vice versa.

The data which is outputted in the time domain from the accelerometer sensor needs first to be transformed into the frequency domain by applying the Fourier transform. The first step towards computing the power spectrum of the gait signal was applied by Rong et al. [106] using the *Discrete Fourier Transform (DFT)*. Another and a faster version of DFT, the *Fast Fourier Transform (FFT)* was further applied by Baechlin et al. [4] and Gafurov [33]. The outcome when applying the DFT/FFT to the acceleration signals results in a set of coefficients. These coefficients are sine and cosine waves of appropriate frequencies. The coefficients determined by the DFT/FFT represent the amplitudes of each of these components, which is used as the feature vector. The main difference between FFT and DFT is the computation time where FFT takes $O(N * log2(N))$ operations, whereas a DFT takes $O(N^2)$ operations.

Figure 2.18 illustrate how a gait signal and its corresponding frequencies are transformed. Once the transform is complete, it is thus possible to derive features from the signal in order to create a template. In [33], the frequency axis was divided into ranges, and the highest amplitude within each range was used as the features, concatenated in a feature vector.

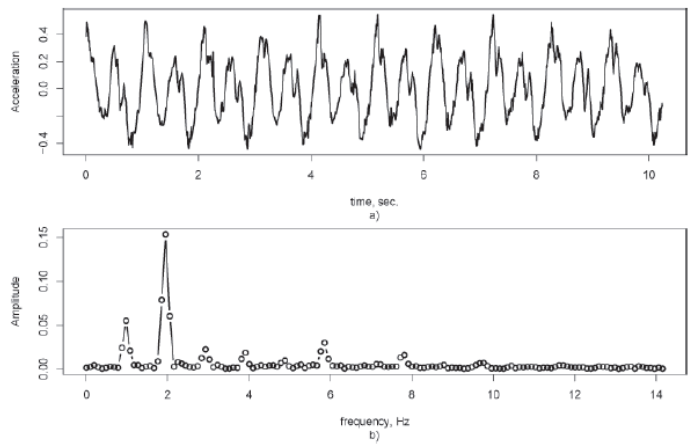


Figure 2.18: Gait signal in time (a) and frequency (b) domain [33].

In work of Ibrahim et al. [49], the *Discrete Cosine Transform (DCT)* is applied. In particular, a DCT is a Fourier-related transform similar to the DFT. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry, where in some variants the input and/or output data are shifted by half a sample. In the work of Ibrahim et al., energy was calculated which was information passed through the DCT to obtain the coefficient of the signal. These coefficients formed the feature vector.

Another method that has many similarities and few strong dissimilarities with FFT is the *Discrete Wavelet transform (DWT)* that was applied by Mostayed et al. [87]. The feature vector in the work was the de-noised signal when applying the the wavelet coefficients to the clear signal.

In Iso et al. [53], the extraction of the spectral features such as the *Wavelet Packet Decomposition (WPD)* was applied. The wavelet packet decomposition (WPD) (sometimes known as just wavelet packets) is a wavelet transform where the signal is passed through multiple filters than the discrete wavelet transform (DWT) as mentioned earlier. Iso et al. criticized the use of FFT stating that FFT was a typical signal processing approach that only provided limited analysis resolution. It was further stated that the WPD was a finer analysis in each frequency range through the use of localized orthogonal basis functions with a splitting algorithms that down-sampled not only the scaling components but also the wavelet components. By using the information criteria of WPD, the decomposed signal was the representative feature of the signal patterns. The periodograms represented the features of the best basis and the momentum of the information entropy distribution of the best basis.

In the work of Bours and Shrestha [14], the principal component analysis (PCA) was applied. The PCA is a statistical technique that, inside biometrics, mainly has been applied to face recognition before, but also VS based gait recognition. In general any multidimensional source of information is expressed in the basis consisting of the unit-vectors. The idea behind PCA [20] is to find new basis vectors that express the underlying dataset best.

Given a dataset, PCA will find new basis vectors such that the first basis vector will contain the most information about the underlying dataset. The next basis vector will contain a little less information, and in fact each following basis vector will contain less information about the dataset as the basis vectors before. The basis vectors are also called eigenvectors and the importance of the basis vectors is expressed in the so called eigenvalues. The number of eigenvalues equals the number of eigenvectors, which is again equal to the number of dimensions in the dataset.

2.3.3.5 Comparison Algorithms

Statistical Approach

To compare two feature vectors with each other we apply a comparison function. A comparison function could be a distance metric function or a similarity function. There are are infinitely many comparison functions to apply and each functions output different results. The comparison function that is used has a major impact on the performance of the authentication system and therefore it is very important to find a good comparison function.

A comparison function that has been applied by Ailisto [1] is the cross-correlation. The cross correlation is a method of estimating the degree to which two feature vectors are the same.

Two almost alike comparison approaches that have been applied in Gafurov [33] and Holien [42] is the *Absolute distance* (mostly known as the Manhattan distance metric) and Euclidean. Absolute distance is a very simple metric that takes the sum of the absolute values of the differences between all the values in the template and the corresponding values in the input. As a result of this, the Absolute distance requires that the template and the input have equal length. It computes the distance that would be traveled to get from one data point to the other if a grid-like path is followed. The equation of the Absolute distance is given:

$$d_{abs.}(X,Y) = \sum_{i=1}^{k} |x_i - y_i|$$

The Euclidean distance is a slight modification of the Absolute distance. Instead of taking the sum of the absolute differences we now take the square root of the sum of all differences squared. This means that it measures the as-the-crow-flies distance between two points. The equation of the Euclidean distance is given:

$$d_{eucl.}(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

A commonly referenced technique with strong reported performance is called Dynamic Time Warping (DTW), this was considered by Holien [42], Mjaaland [84] and Derawi [27]. DTW is an algorithm for measuring similarity between two feature vectors which may vary in time or speed. It can be used for slight variations of speed within a cycle. Generally spoken, the DTW is an approach that allows to find an optimal comparison between two given feature vectors with certain restrictions. Unlike other distance metric like the Absolute or Euclidean metrics which both takes as input feature vectors of the same length, the Dynamic Time Warping does not have that restriction.

Machine learning approach

The supervised learning in wearable gait recognition is a machine learning approach used to get measures of a function derived from gait signal training data. The output of the supervised learning function predicts a class label of the input known as classification.

Different approaches have been applied for regression and classification in wearable gait recognition. The first example introduced in this subsection is the use of *Support Vector Machine (SVM)* which was applied by Sprager et al. [112] to identify gait. The classification was performed with machine learning tool, WEKA [104]. For the classification a kernel function of n-order and a complexity parameter was used. The latest work performed on accelerometer based recognition was performed by Nickel et al. [90].

Another applied classification approach by Sprager et al. [112] used the *Principal Component Analysis (PCA)* to actually find out how similar walking patters are. PCA was performed using *Singular Value Decomposition (SVD)* on the feature vector created. For this, the *Karhunen-Loeve* transformation was applied.

Annadhorai et al. [3] applied *Linear Discriminant Analysis (LDA)* to select the best features prior to classification. The features with the highest weighting in the LDA projection matrix were given to the classifier that increased the classification accuracy of the system. Furthermore, the *k-Nearest Neighbor (k-NN)* classifier was used for gait identification. The k-NN classifier was chosen for its simplicity, scalability and small memory requirements.

Sazanov et al. [107] applied a multilayer perception (MLP) *neural network* as the pattern classifier. The MLP uses hyperplanes to separate layers into different classes and consist of three parts: The input layer, hidden layer, and output layer. The inputs to the network are the determined feature vectors. The outputs of the system are the classes related to the users.

Iso et al. [53] proposes a fuss-free gait analyzer for healthcare. The applied methodology, the *Kohonen self-organizing map (KSOM)* for deciding cluster borders on the learned feature vector, and Bayesian theory was applied to improve the results.

2.3.3.6 Performance Evaluation

Comparing gait performances

There is no public data-set available for WS-based gait, in contrast to video-based gait biometric. This complicates the issue of comparing the results obtained on various private-sets with each other. We cannot consider any direct comparison of obtained results. Nevertheless, a short summary of the current WS-based gait recognition studies from years 2004 to 2012 is shown in Table 2.5. In the last column, #TP, is represented the number of subjects that contributed to the test data set.

Study	EER	Recognition	#TP
Huang et al. [44]	-	96.93 %	9
Morris [86]	-	97.4 %	10
Rong et al. [106]	5.6 %	-	21
Frank et al. [106]	-	100 %	25
Gafurov [33]	5 %	-	30
Vildjiounaite et al. [120]	13.7 %	-	31
Ailisto et al. [1]	6.4 %	-	36
Ailisto et al. [2]	7.0 % , 19.0 %	-	36
Nickel et al. [90]	10%	-	36
Bours and Shrestha [14]	1.68%	-	60
Derawi et al. [27]	5.7%	-	60
Holien et al. [42]	5.9%	-	60

Table 2.5: Performances of current wearable sensor-based gait recognitions

2.4 Activity Recognition

Gait recognition is to recognize the person from the collected accelerometer data. Activity recognition is to recognize a specific activity from the collected accelerometer data. Both can be combined to first detect what kind of specific walking (fast, normal, slow, running, etc) a user is doing or if the user is not performing a walking related activity (for example sitting, standing, cycling, or sleeping).

Activity recognition is the process of identifying everyday common human activities. It is a recently new area of study. Accelerometers are integrated in new mobile devices such as smart phones, tablet computers, digital audio players (Ipod) etc., which can be used to record the body motion. The majority of studies for activity recognition are performed by using wearable sensors. In the following we will give details about the sensors that have been used for activity recognition and which activities that were considered for identifying human activities.

Due to many different application areas of activity recognition, there is no surprise that the list of activities that many researchers have tried to recognize with various sensors is long.
According to [45], activities can be categorized in three groups based on duration and/or complexity: *Gestures (or Movement/Motif)*, *Low-Level Activities*, and *High-Level Activities*. Activities such as walking, sitting, standing, eating, cleaning windows are considered as low-level activities which usually last between seconds and several minutes. As high-level activities are considered activities like sight-seeing, cleaning the house, working at office that usually last for more than a few minutes and up to a few hours. Figure 2.19 illustrates these groups of activities.

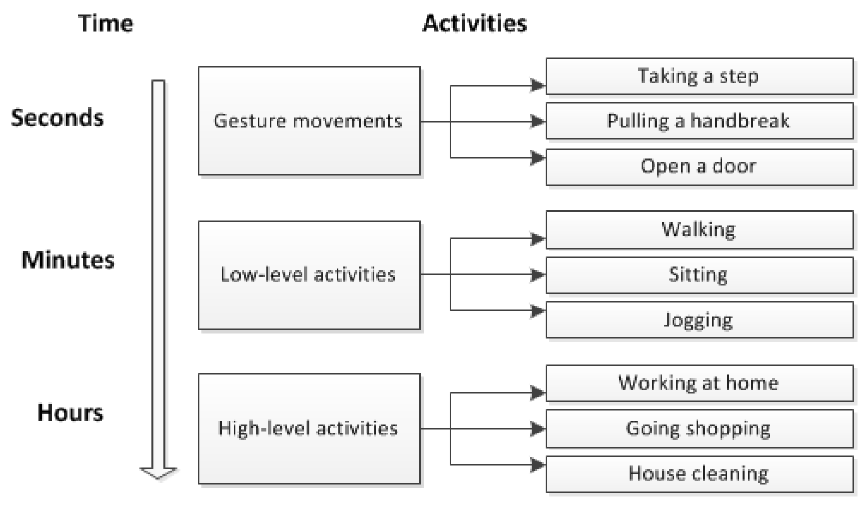


Figure 2.19: Level of Activitities [45]

The way accelerometer data for activity recognition is processed is similar to the way gait data is processed, which is illustrated in 2.6. Because of this similarity we will give only a brief description of activity recognition.

2.4.1 Activities

The identification of everyday routine and leisure activities such as walking, running, biking, sitting, climbing and lying have already been analyzed in laboratory settings by several researchers. All these studies were done by using different sensors such as accelerometers, which were embedded in wearable sensing devices to collect the needed data. The types of sensors used for activity recognition will be mentioned in the next section. Accelerometer sensors are very useful for low-powered equipment like smart phones or tablet computers, with applications that are suitable for real-time detection of user's activities. Physical activities such as walking, going up/down stairs, standing, sitting, and running have been studied by some of the researchers using different accelerometers sensors. Table 2.6 gives an overview of some of the databases that has been collected.

Table 2.6: Activity recognition research studies. #TP = Test Persons

Study	Activities	#TP
[123]	walking flat, walking slope-up, walking stairs slope-down	52
[62]	walking, walking stairs, sitting, jogging, standing	29
[79]	walking, sitting, standing	26
[75]	walking, running, cycling	24
[3]	walking, running, sitting, standing, cycling	20
[49]	walking, climbing stairs	15
[92]	walking, running, sitting and standing, lying down	12
[70]	walking, walking stairs, sitting, standing, riding elevator up/down, and brushing teeth	12
[37]	walking, running, still, jumping	11
[115]	walking, waiting at a tram stop, sitting, riding a tram	8
[117]	walking, walking stairs, standing, sitting and running	6
[58]	walking, walking stairs, sitting, running	6
[127]	walking, running, standing, climbing	5
[38]	walking, running, sitting, standing, lying	5
[71]	walking, walking stairs, jogging, sitting riding a bike	2

Another class of activities, mainly studied in healthcare environments, are the so-called "Activities of Daily Living" (ADLs). ADLs include activities such like bathing, toileting, dressing, eating which are basic skills needed for daily self-care activities. A third class which is an extension to ADL is known as the "Instrumental Activities of Daily Living" (IADLs), which are skills beyond basic self-care which a person needs to perform for independent living. IADLs include activities like shopping, driving, cleaning, cooking, doing laundry and managing money. Table 2.7 shows an overview of these activities.

Table 2.7: Studies of activity recognition of daily living (ADL)

Study	Activities (ADL)	#TP
[100]	toileting, washing, housework, leisure activity, oral hygiene, heating use, taking medication, etc.	14
[113]	mopping, cleaning windows, making bed, watering plants, washing dishes, setting the table, vacuuming, ironing, dusting	12
[30]	lying, rowing, cycling (training,regular), sitting, standing, running, walking, football	12
[88]	prepare food, clean dishes, wash clothes	10
[20]	showering, urination, flushing, washing Hands, defecation, brushing teeth	4
[116]	prepare food, toileting, bathing, dressing, grooming, preparing a beverage, doing laundry, etc.	2
[124]	prepare different food, eat cereal, dust, brush teeth, tend plants, set table, clean windows, take medication, shower, shave	2

2.4.2 Data Acquisition

As mentioned earlier, accelerometer sensors are adequate and most commonly used for continuous activity recognition. They are also considered to be less intrusive than other sensors such as RFID gloves, microphones, and cameras [45]. Therefore, accelerometers are becoming very important tools due to many advantages in activity recognition. There is not a single sensor that can record all the body movements and recognize all different human activities. As a result most research today have been using different sensors to capture the data or attached multiple sensors on various parts of the body such as hip, wrist, arm, ankle, chest, thigh or knee. For instance, activities like walking fast, walking slow, and running can be recognized by motion sensors (accelerometer or gyroscope) but these sensors cannot recognize activities such as, talking or reading. Table 2.8 gives an overview of some of the most widely used sensors for activity recognition research.

Table 2.8: Sensors used in different studies.

Study	Sensor Placement	Sensor
[57]	Above ankle, above knee, hip, wrist, elbow,	3D Accelerometer (ADXL311)
[78]	Belt (left/right)	3D Accelerometer ADXL202
[6]	Chest	3D Accelerometer (ADXL213, analog)
[5]	Hip, thigh, ankle, arm, wrist	2D Accelerometer (ADXL210E, analog)
[65]	Legs	2D accelerometer (ADXL202JE, analog) and Ball Switches
[119]	Legs (upper), above knee	1D Accelerometer (ADXL05s, analog) , passive infrared sensors, carbon monoxide sensor, microphones, pressure sensors, temperature sensors, touch-sensors and light-sensors
[103]	Near pelvic region	3D Accelerometer (CDXL04M3)
[37]	Pocket	3D Accelerometer (ADXL330, analog)
[62]	Pocket	3D Accelerometer (Cell phone)
[102]	Pocket	2D Accelerometer (ADXL202), GPS
[9]	Waist	3D Accelerometer
[126]	Waist	3D Accelerometer and a microphone.
[108]	Waist belt	3D Accelerometer
[46]	Wrist, hip and thigh	2D accelerometer (ADXL202JE), Tilt switches

Other sensors that have been used for activity recognition are: Sociometer (IR transceiver, a microphone, two accelerometers, on-board storage, and power supply) [22], GPS sensors [30], vision sensors (i.e., cameras) [30, 94], microphones [20, 47], RFID tag readers [98, 100, 113], ball switches [65], fibber optical sensors [29], gyroscope [61], body and skin temperature sensors [119, 73, 59, 128, 92], light sensors [119, 73, 80, 101], foam pressure sensors [15], pressure sensors [73], physiological sensors [96], humidity and barometric sensors [73].

2.4.3 Activity Recognition Process

2.4.3.1 Segmentation

Detection of activities from the collected data is the process of finding the ”boundaries” for different activities in the accelerometer signal. Segmentation is a necessary step in the data analysis process before the feature extraction and the classification. Several segmentation techniques have been used to identify different activities from the sensor data. Some of the segmentation methods that have been used for activity recognition are: ”Sliding Windows”, ”Top-Down”, ”Bottom-Up” and ”Sliding Window and Bottom-Up (SWAB)” [56].

2.4.3.2 Feature Extraction

The input data recorded with the sensors from the human body motions is too large for processing for personal computers, thus it is easier as an initial step to transform the large amount of input data into a reduced representation set of features before further processing. The process of transforming the large amount of input data into the set of features is called feature extraction. Feature extraction is a very important step; therefore features should be carefully chosen in order to extract relevant information from the input data, which features are selected will have a strong influence in the results of the classification. Feature selection is an important and essential step in the design of any activity recognition system, in order to have an effective system. The features in different studies were analyzed mainly in time-domain and frequency-domain. In the following we will brief describe features extraction in both domains.

Features in the time domain

In many of the research only the time-domain features were considered to avoid the transformation complexity which required a transform of the time-domain signal into frequencies. They consume little processing power and the algorithms can be applied directly.

In the studies of Laerhoven and Cakmakci [64, 5], the average value was one of the values applied as a feature for identifying activities. The average, indicated by μ, is the mean value of a signal. It is found by adding all of the samples together, and divide by N, indicating the number of samples. In a mathematical form it is as in Equation 2.8:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{2.8}$$

Two closely related features to the mean that are often used are the standard deviation and variance by Kern et al. [57] and Heinz et al. [39], respectively. The standard deviation gives an idea of how close the entire set of signal data is to the average value, μ. In equation form, the standard deviation is calculated as in Equation 2.9.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^2 \tag{2.9}$$

Another similar feature to the mean, is the root mean square (RMS). This has been used by Maurer et al. [80]. The RMS value of a signal is the square root of the mean value (μ) of the squares of the original values (or the square of the function that defines the signal). Given a signal set of N values, the Equation 2.10 shows how the RMS is calculated.

$$rms = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{2.10}$$

Lombriser et al. [74] has used the zero or mean crossing rate as a feature. In the context of signals, a zero crossing is said to occur if successive samples have different algebraic signs. The rate at which zero crossings occur is a simple measure of the frequency content of a signal. Zero-crossing rate is a measure of number of times in a given time interval/frame that the amplitude of the speech signals passes through a value of zero as shown in Figure 2.20. This also follows for the mean crossing rate, except that the mean is used instead of zero passing.

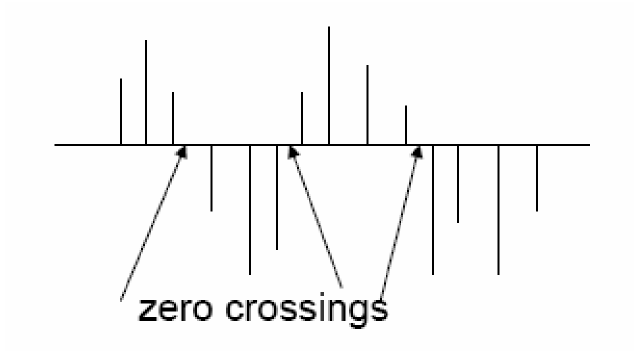


Figure 2.20: Zero Crossing Rate [74]

The zero crossing rate was also applied of Chambers et al. [19]. Instead thee extracted the features from the accelerometer data using the ZCR of the first and second derivatives to retrieve even more features.

Amplitude peak counting is also a feature that could be used. Laerhoven et al. [65] performed a peak extraction, where the number of peaks in different windows sized were counted on a signal.

Features in the frequency-domain

Simple statistical descriptors, as we saw in the section before, are widely used; the variance is computed by taking the average of the squared data samples. Frequency-domain features can be derived from several approaches, for example, the FFT-coefficients, energy and spectral entropy.

The signal energy in a signal processing context is not the same as the conventional notion of energy in physics and the other sciences. The two concepts are, however, closely related. The signal energy have been extracted by Stikic et al. [114] and in signal processing, the energy E_s of a signal $x(t)$ is defined in Equation 2.11.

$$E_s = \int_{\infty}^{-\infty} |x(t)|^2 \tag{2.11}$$

Other features can be derived from the coefficients of time-frequency transforms, like the Fast Fourier Transform (FFT), Short Time Frequency Transform (STFT) or the Discrete Wavelet Transform (DWT) [77].

Even the frequency-domain entropy is helpful in discriminating primitives that differ in complexity. As a matter of fact, walking can be difficult to discriminate based on energy features; however, the different walking entropy such as walking fast turns out to be much higher than the walking slow entropy, mainly because of the acceleration impacts, which give rise to the distinctive high-frequency colored noise-like signatures typically observed in the signals from on-body accelerometers. Several studies, Wang et. al [124] and Stikic et al. [113] have applied entropy as one of the features to be used.

2.4.3.3 Classification process

The next step after the feature extraction is the classification process. In the classification process, the classification algorithm builds up a model (classifiers) for different human activities and then uses these classifier to identify human activities from the test data. A wide range of machine learning approaches and algorithms are used for activity recognition.

Most of these approaches have been used for activity recognition which can be categorized into two groups: supervised learning and unsupervised learning.

Supervised learning is a machine learning technique, also sometimes called ”learning with a teacher” in which the system is first trained by using a set of labeled training data. In the next step unknown (unlabeled) data is presented to the system that will classify it based on the learned information. There are two general phases in a supervised learning technique: training and testing. During the training phase the system is taught (trained) by using a set of training data to create a classification model to classify unknown data. During the testing phase, the model of the system is tested using a set of test data to measure the classification accuracy [72]. Training and testing phases are illustrated in Figure 2.21. The

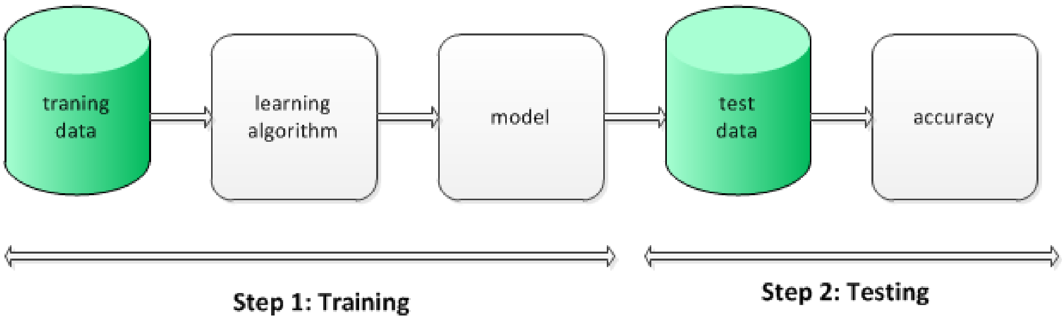


Figure 2.21: The basic of learning process: training and testing [72]

majority of work that has been done within activity recognition have been done by using supervised learning methods. A summary of these supervised learning approaches applied in activity recognition so far is shown in Table 2.9.

Table 2.9: Supervised learning approaches used for activity recognition

Study	Approaches
[103]	Naive Bayes Classifier
[5]	C4.5 Decision Tree
[61]	Nearest Neighbor
[98]	Hidden Markov Model
[46]	Support Vector Machine
[119]	Kohonen Self-Organising Map

Unsupervised learning, by contrast, does not split the available data in a training and testing set. Instead, it tries to classify the unknown data by separating the data into different classes (clusters). It is a ”learning without teacher” method. The method tries to directly build models not basing itself on any priori-built model or knowledge. The task is to discover classes of similar examples from the unlabeled data and to organize the data into similarity groups, which are known as clusters, or to estimate the distribution of data within the input space which is called density estimation [10]. Clustering is the process of organizing unlabeled data into clusters, where the data in the same cluster are similar to each other and the data in different clusters are dissimilar [18].

A summary of the unsupervised learning approaches that are applied for activity recognition is shown in Table 2.10.

2.4.4 Activity Recognition Accuracies

Studies have shown different accuracies for activity recognition systems in which the data collection was performed in a controlled laboratory setting (subjects are told what activity

Table 2.10: Unupervised learning approaches used for activity recognition

Study	Approaches
[83]	Hidden Markov Model (HMM)
[23]	Hierarchies of HMM
[99]	Hierarchical Dynamic Bayesian Network
[105]	Multiple Eigenspaces
[89]	Gaussian Mixture Models
[76]	Multi-layered FSM

to perform), from the experiments in which the data was collected under normal circumstances (naturalistic environment).

A summary of recognition accuracies is shown in the Table 2.11.

Table 2.11: Recognition Accuracies. #TP = Test Persons. L = Laboratory setting, N = Normal circumstance

Study	Accuracy	Activities	Environment	#TP
[75]	80%	walking, running, cycling, driving, sports	N	24
[5]	84%	walking, sitting, standing, running, computer work, bicycling, Lying down, etc.	N	20
[78]	83% - 90%	walking, downstairs, upstairs, opening doors	L	6
[81]	90%	walking, jogging, upstairs, downstairs, sitting, standing	L	29
[55]	90.8%	walking (slow, normal, fast), sitting, standing, lying, falling	L	6
[69]	92.85% - 95.91%	sitting, standing, walking,	L	8
[57]	65% - 95%	sitting, standing, walking, stairs up/down, whiteboard writing, shake hands, keyboard typing	N/L	1
[37]	97,51%	walking, jumping, still, running	L	11
[38]	99,5%	standing, sitting, lying, walking, running	L/N	5

2.5 Mobile Phones and Biometrics

Mobile phones are no longer devices that are just for the purpose of communication. People use them for surfing the web, paying for products and services as well as storing sensitive data and information. All such mobile phone utilities demand adequate level of security. Mobile phones need to be protected from unauthorized access and biometric techniques are being evaluated to provide safety and security of mobile phones.

There are several concerns related to mobile phone security and biometric systems can address each one of them;

Information Loss Most of the mobile phone users are concerned about the risks involved in storage of information in their devices. Biometrics helps solve the issues by providing features like phone locks and content locks. In general, access control can be taken care of by implementation of a biometric system in a mobile phone.

Phone Theft Another concerning issue is related to the possible theft and misuse of cell phones. Phone locks and personalized number dialers are some of the options that biometric systems offer to prevent cell phone misuse even if the device is stolen.

Mobile Services Usage A last concern is related to the security of mobile banking and mobile commerce activities that are gaining popularity in todays world. Cell phone users are increasingly using of their devices to make payments and to use a variety of commercial services. Payment authorization and e-Wallet personalization are some of the features associated with biometric e-Commerce or what can be called mobile commerce.

Biometric systems can be integrated in mobile phones in two ways: 1) as an on-line device or 2) as a off-line stand-alone system, to protect unauthorized use of the mobile phone. In the first case, cell phones are collecting data and passes it online via the Internet to a remote location where it is processed and compared. This proves useful for remote transactions when the identity of the caller has to be proven. As an example when a user calls his/her bank to make a transaction, she is going to introduce herself as Alice Bobson and in order to verify her identity she is asked to recite a pass-phrase. The voice recording is then processed and compared to the sample that was collected when the user enrolled in the system. Face, fingerprint, signature, gait, gesture or keystroke are other biometric traits that todays cell phones have the capabilities to collect and transfer them to a remote location.

In the second possible implementation of a biometric system on a mobile phone, the entire biometric system resides on the mobile phone and it serves the purpose of preventing unauthorized access to cell phone functions and data. Biometric systems can replace PIN security and for example with a swipe of a finger the phone can be unlocked and used. Todays implementations of biometric systems on cell phones include fingerprint recognition, voice recognition, face recognition, signature recognition, gait recognition, gesture-recognition and keystroke dynamics.

Use and implementation of biometrics in mobile phones is further enhanced by combining the technology with existing mobile phone security arrangements. For instance, a mobile phone user may have to authorize his mobile banking transactions through biometric recognition as well as using passwords and SMS codes. This is indeed a more and more elaborate security arrangement for the people who are highly dependent upon mobile phones for a variety of purposes that demand high-end security.

Previous research on using biometrics in mobile phones had already been introduced before. In 2005, Cho et al. [21] proposed a pupil and iris localization algorithm, which is apt for mobile phone platform based on detecting dark pupil and corneal specular reflection by changing brightness and contrast value. A year after, Okumura et al. [95] proposed a system where a subject could authenticate himself/herself by grasping and shaking the phone. In this study a normal accelerometer with the size of a mobile phone was used. In 2007, Hadid et al. [36] described and analyzed a face authentication system for person authentication by attaching the camera of the phone in front of the subjects face. At the same year a prototype was designed on how microphone in a mobile phone and its camera could perform voice and fingerprint recognition [110]. This work was continued by Wang et al [121] in 2009, who fused these two biometric features together retrieving acceptable results. At the same year gait recognition started to get familiar as can be read throughout the thesis. In 2011, Conti et al. [24] proposed a biometric measure to authenticate the user of a smartphone i.e. the movement the user performs when answering (or placing) a phone call.

2.6 Bibliography

[1] AILISTO, H. J., LINDHOLM, M., MANTYJARVI, J., VILDJIOUNAITE, E., AND MAKELA, S.-M. Identifying people from gait pattern with accelerometers. *In Proceedings of the SPIE 5779* (2005), 7–14. 22, 29, 32, 33, 78, 80, 81, 82, 132, 133, 134

[2] AILISTO, H. J., LINDHOLM, M., MNTYJRVI, J., VILDJIOUNAITE, E., AND MKEL, S.-M. Identifying people from gait pattern with accelerometers. *Biometric Technology for Human Identification II 5779*, 1 (2005), 7–14. VTT Electronics, Finland. 20, 22, 33, 77, 78, 80, 82

[3] ANNADHORAI, A., GUENTERBERG, E., BARNES, J., HARAGA, K., AND JAFARI, R. Human identification by gait analysis. In *HealthNet '08: Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments* (New York, NY, USA, 2008), ACM, pp. 1–3. 22, 33, 35, 78, 80, 81, 131, 133, 134, 135, 137, 148

[4] BAECHLIN, M., SCHUMM, J., ROGGEN, D., AND TÖSTER, G. Quantifying gait similarity: User authentication and real-world challenge. In *ICB '09: Proceedings of the Third International Conference on Advances in Biometrics* (Berlin, Heidelberg, 2009), Springer-Verlag, pp. 1040–1049. 22, 30, 77, 78, 80, 132, 133, 134, 135

[5] BAO, L., AND INTILLE, S. S. Activity Recognition from User-Annotated Acceleration Data. *Pervasive Computing* (2004), 1–17. Available from: `http://www.springerlink.com/content/9aqflyk4f47khyjd`. 36, 37, 39, 40, 82, 83

[6] BARRALON, P., NOURY, N., AND VUILLERME, N. Classification of daily physical activities from a single kinematic sensor. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference 3* (2005), 2447–2450. Available from: `http://dx.doi.org/10.1109/IEMBS.2005.1616963`. 36, 133

[7] BBC-NEWS. How can you identify a criminal by the way they walk? Available from: `http://news.bbc.co.uk/2/hi/uk_news/magazine/7348164.stm`. 18

[8] BENABDELKADER, C., CUTLER, R., AND DAVIS, L. Stride and cadence as a biometric in automatic person identification and verification. In *FG'02* (2002), pp. 372–377. 18, 195

[9] BIDARGADDI, N., KLINGBEIL, L., AND SARELA, A. Detecting walking activity in cardiac rehabilitation by using accelerometer. *Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on* (2007), 555–560. Available from: `http://dx.doi.org/10.1109/ISSNIP.2007.4496903`. 36, 133

[10] BISHOP, C. M. *Pattern Recognition and Machine Learning*. 2006. 39, 135

[11] BOBICK, A. F., AND JOHNSON, A. Y. Gait recognition using static, activity-specific parameters. In *CVPR 2001* (2001), vol. 1. 18, 195

[12] BOUCHRIKA, I., AND NIXON, M. S. Model-based feature extraction for gait analysis and recognition. In *Mirage: Computer Vision ? Computer Graphics Collaboration Techniques and Applications* (March 2007), vol. 4418, pp. 150–160. 18, 195

[13] BOURS, P. *Authentication course, IMT 4721*. Gjøvik University College, September 2006. xiii, 7, 8, 9, 10

[14] BOURS, P., AND SHRESTHA, R. Eigensteps: A giant leap for gait recognition. In *2nd International Workshop on Security and Communication Networks (IWSCN 2010)* (Karlstad, Sweden, 5 2010). 31, 33, 82, 132

[15] BRADY, S., DUNNE, L. E., TYNAN, R., DIAMOND, D., SMYTH, B., AND O'HARE, G. M. P. Garment-based monitoring of respiration rate using a foam pressure sensor. In *Proceedings of the Ninth IEEE International Symposium on Wearable Computers* (Washington, DC, USA, 2005), IEEE Computer Society, pp. 214–215. Available from: `http://portal.acm.org/citation.cfm?id=1104998.1105315`. 36

[16] BUVARP, T. E. Hip movement based authentication. Master's thesis, Gjøvik University College NISlab, 2006. 20

[17] CanadaNews. Forensic gait analysis points to accuse. Available from: http://www.canada.com/victoriatimescolonist/news/story.html?id=19d99f1a-bb4d-4d89-a92e-e7a583b1d14f. 18, 134, 135

[18] Carey, Michael J., C. S. *Data-Centric Systems and Applications*. 2006. 39, 135

[19] Chambers, G. S., Venkatesh, S., West, G. A. W., and Bui, H. H. Hierarchical recognition of intentional human gestures for sports video annotation. In *16th International Conference on Pattern Recognition* (2002), vol. 2, pp. 1082–1085. Available from: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1048493. 38

[20] Chen, J., Kam, A. H., Zhang, J., Liu, N., and Shue, L. Bathroom Activity Monitoring Based on Sound. 2005, pp. 47–61. Available from: http://dx.doi.org/10.1007/11428572_4. 35, 36

[21] Cho, D. H., Park, K. R., and Rhee, D. W. Real-time iris localization for iris recognition in cellular phone. In *Proceedings of the Sixth International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing and First ACIS International Workshop on Self-Assembling Wireless Networks* (Washington, DC, USA, 2005), SNPD-SAWN '05, IEEE Computer Society, pp. 254–259. 41

[22] Choudhury, T., and Pentland, A. Sensing and modeling human networks using the sociometer. In *Proceedings of the 7th IEEE International Symposium on Wearable Computers* (Washington, DC, USA, 2003), ISWC '03, IEEE Computer Society, pp. 216–. Available from: http://portal.acm.org/citation.cfm?id=946249.946901. 36

[23] Clarkson, B., and Pentland, A. Unsupervised clustering of ambulatory audio and video. In *ICASSP '99: Proceedings of the Acoustics, Speech, and Signal Processing, 1999. on 1999 IEEE International Conference* (Washington, DC, USA, 1999), vol. 6, IEEE Computer Society, pp. 3037–3040. Available from: http://dx.doi.org/10.1109/ICASSP.1999.757481. 40, 135

[24] Conti, M., Zachia-Zlatea, I., and Crispo, B. Mind how you answer me!: transparently authenticating the user of a smartphone when answering or placing a call. In *Proceedings of the 6th ACM Symposium on Information, Computer and Communications Security* (New York, NY, USA, 2011), ASIACCS '11, ACM, pp. 249–259. Available from: http://doi.acm.org/10.1145/1966913.1966945. 41

[25] Cutting, J., . K. L. Recognizing friends by their walk: Gait perception without familiarity cues. *Bull. Psychon. Soc. Vol. 9* (1977), pp. 353–356. 18, 195

[26] Derawi, M. O., Bours, P., and Holien, K. Improved cycle detection for accelerometer based gait authentication. In *International Conference on Intelligent Information Hiding and Multimedia Signal Processing - Special Session on Advances in Biometrics* (2010). 25, 27, 29, 54, 57, 225, 227

[27] Derawi, M. O., Bours, P., and Holien, K. Improved cycle detection for accelerometer based gait authentication. In *International Conference on Intelligent Information Hiding and Multimedia Signal Processing - Special Session on Advances in Biometrics* (2010). 32, 33, 78, 80, 81, 82, 132

[28] Derawi, M. O., Nickel, C., Bours, P., and Busch, C. Unobtrusive user-authentication on mobile phones using biometric gait recognition. *Intelligent Information Hiding and Multimedia Signal Processing, International Conference on 0* (2010), 306–311. 20, 22, 138

[29] Dunne, L., Walsh, P., Smyth, B., and Caulfield, B. Design and evaluation of a wearable optical sensor for monitoring seated spinal posture. *Wearable Computers, IEEE International Symposium 0* (2006), 65–68. 36

[30] Ermes, M., Pärkka, J., Mantyjarvi, J., and Korhonen, I. Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. *IEEE transactions on information technology in biomedicine : a publication of the IEEE Engineering in Medicine and Biology Society 12*, 1 (Jan. 2008), 20–26. Available from: `http://dx.doi.org/10.1109/TITB.2007.899496`. 35, 36

[31] Frank, J., Mannor, S., and Precup, D. Activity and gait recognition with time-delay embeddings. In *AAAI Conference on Artificial Intelligence* (2010). Available from: `http://www.aaai.org/ocs/index.php/AAAI/AAAI10/paper/view/1666`. 20, 22, 82, 83

[32] Frank, J., Mannor, S., and Precup, D. Data sets: Mobile phone gait recognition data, 2010. Available from: `http://www.cs.mcgill.ca/~jfrank8/data/gait-dataset.html`. 20

[33] Gafurov, D. *Performance and Security Analysis of Gait-based User Authentication*. Ph.D. thesis, Faculty of Mathematics and Natural Sciences, University of Oslo, 2008. ix, 17, 20, 22, 25, 27, 29, 30, 31, 32, 33, 77, 78, 80, 81, 82

[34] Gafurov, D., Snekkenes, E., and Bours, P. Improved gait recognition performance using cycle matching. *Advanced Information Networking and Applications Workshops, International Conference on 0* (2010), 836–841. 29

[35] Geradts, Z. J., Merlijn, M., de Groot, G., and Bijhold, J. Use of gait parameters of persons in video surveillance systems. Z. J. Geradts and L. I. Rudin, Eds., vol. 4709, SPIE, pp. 16–24. Available from: `http://link.aip.org/link/?PSI/4709/16/1`. 17

[36] Hadid, A., Heikkila, J., Silven, O., and Pietikainen, M. Face and eye detection for person authentication in mobile phones. In *Distributed Smart Cameras, 2007. ICDSC '07. First ACM/IEEE International Conference on* (sept. 2007), pp. 101 –108. 41

[37] He, Z., and Jin, L. Activity recognition from acceleration data based on discrete consine transform and svm. In *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on* (2009), pp. 5041 –5044. 35, 36, 40, 129, 131, 133, 137, 147, 148

[38] hee Lee, M., Kim, J., Kim, K., Lee, I., Jee, S. H., and Yoo, S. K. Physical activity recognition using a single tri-axis accelerometer. In *Proceedings of the World Congress on Engineering and Computer Science 2009 Vol I, WCECS '09, October 20 - 22, 2009, San Francisco, USA* (2009), S. I. Ao, C. Douglas, W. S. Grundfest, and J. Burgstone, Eds., Lecture Notes in Engineering and Computer Science, International Association of Engineers, Newswood Limited, pp. 14–17. 35, 40, 131, 134, 137

[39] Heinz, E. A., Kunze, K.-s., Sulistyo, S., Junker, H., Lukowicz, P., and Tröster, G. Experimental evaluation of variations in primary features used for accelerometric context recognition. In *in Proceedings of the 1st European Symposium on Ambient Intelligence (EUSAI 2003* (2003), vol. 1, pp. 252–263. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.72.6282`. 37

[40] Henriksen, M., Lund, H., Moe-Nilssen, R., Bliddal, H., and Danneskiod-Samse, B. Test-retest reliability of trunk accelerometric gait analysis. *Gait Posture 19*, 3 (2004), 288–97. Available from: `http://www.biomedsearch.com/nih/Test-retest-reliability-trunk-accelerometric/15125918.html`. 20, 22, 77, 78

[41] HERSCHEL, W. *The origin of finger-printing*. H. Milford, Oxford University Press, 1916. Available from: `http://books.google.no/books?id=Q_5UAAAAMAAJ`. 9

[42] HOLIEN, K. Gait Recognition under non-standard circumstances, Master thesis, Gjøvik University College, 2008. ix, 20, 21, 22, 23, 24, 25, 26, 27, 32, 33, 77, 78, 80, 81, 82, 133, 135

[43] HU, W., TAN, T., WANG, L., AND MAYBANK, S. A survey on visual surveillance of object motion and behaviors. *IEEE–J–SMCC 34*, 3 (2004), 334–352. 17, 195

[44] HUANG, B., CHEN, M., HUANG, P., AND XU, Y. Gait modeling for human identification. In *International Conference on Robotics and Automation* (2007), pp. 4833–4838. 33, 82

[45] HUYNH, D. T. G. *Human Activity Recognition with Wearable Sensors*. Ph.D. thesis, TU Darmstadt, Darmstadt, September 2008. Available from: `http://tubiblio.ulb.tu-darmstadt.de/38560/`. ix, xi, 34, 36, 129, 130, 131, 147, 156

[46] HUYNH, T., BLANKE, U., AND SCHIELE, B. Scalable recognition of daily activities with wearable sensors. In *3rd International Workshop on Location- and Context- Awareness (LoCA 2007)* (september 2007), p. 50–67. 36, 39

[47] HUYNH, T., AND SCHIELE, B. Unsupervised discovery of structure in activity data using multiple eigenspaces. In *2nd International Workshop on Location- and Context-Awareness (LoCA 2006)* (Dublin, Ireland, May 2006). 36

[48] HYNES, M., WANG, H., AND KILMARTIN, L. Off-the-shelf mobile handset environments for deploying accelerometer based gait and activity analysis algorithms. *Conf Proc IEEE Eng Med Biol Soc 1* (2009), 5187–90. Available from: `http://www.biomedsearch.com/nih/Off-shelf-mobile-handset-environments/19964383.html`. 22, 77, 78

[49] IBRAHIM, R., AMBIKAIRAJAH, E., CELLER, B., LOVELL, N., AND KILMARTIN, L. Gait patterns classification using spectral features. In *IET Irish Signals and Systems Conference (ISSC)* (2008). 31, 35, 80, 131, 148

[50] IKEDA, T., ISHIGURO, H., AND NISHIMURA, T. People tracking by fusing different kinds of sensors, floor sensors and acceleration sensors. In *Multisensor Fusion and Integration for Intelligent Systems, 2006 IEEE International Conference on* (sept. 2006), pp. 530 –535. 17

[51] ISO. Iso/iec 2nd wd 29115: 2008-02-12. 7

[52] ISO. Iso/iec jtc 1/sc 37 n 1991, final text of tr 24741, biometrics tutorial: 2007-02-27. 9

[53] ISO, T., AND YAMAZAKI, K. Gait analyzer based on a cell phone with a single three-axis accelerometer. In *MobileHCI '06: Proceedings of the 8th conference on Human-computer interaction with mobile devices and services* (New York, NY, USA, 2006), ACM, pp. 141–144. 22, 31, 33, 78, 80, 81

[54] JAIN, A. K., ROSS, A., AND PRABHAKAR, S. An introduction to biometric recognition. *IEEE Trans. on Circuits and Systems for Video Technology 14* (2004), 4–20. 9

[55] KARANTONIS, D. M., NARAYANAN, M. R., MATHIE, M., LOVELL, N. H., AND CELLER, B. G. Implementation of a Real-Time Human Movement Classifier Using a Triaxial Accelerometer for Ambulatory Monitoring. *Information Technology in Biomedicine, IEEE Transactions on 10*, 1 (2006), 156–167. Available from: `http://dx.doi.org/10.1109/TITB.2005.856864`. 40, 137

[56] KEOGH, E. J., CHU, S., HART, D., AND PAZZANI, M. J. An online algorithm for segmenting time series. In *Proceedings of the 2001 IEEE International Conference on Data Mining* (Washington, DC, USA, 2001), ICDM '01, IEEE Computer Society, pp. 289–296. Available from: `http://portal.acm.org/citation.cfm?id=645496.657889`. 36, 132

[57] KERN, N., SCHIELE, B., AND SCHMIDT, A. Multi-Sensor Activity Context Detection for Wearable Computing. In *In Proc. EUSAI, LNCS* (2003), vol. 2875, pp. 220–232. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.6.3308`. 36, 37, 40

[58] KHAN, A. M., LEE, Y. K., LEE, S. Y., AND KIM, T. S. Human Activity Recognition via an Accelerometer-Enabled-Smartphone Using Kernel Discriminant Analysis. pp. 1–6. Available from: `http://dx.doi.org/10.1109/FUTURETECH.2010.5482729`. 35, 131

[59] KRAUSE, A., MÜNCHEN, T. U., AND SMAILAGIC, A. Unsupervised, dynamic identification of physiological and activity context in wearable computing. In *In Proceedings of the 7th International Symposium on Wearable Computers* (2003), pp. 88–97. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.135.5809`. 36

[60] KUMAR NEELESH, KUNJU NISSAN, K. A. S. B. S. Active marker based kinematic and spatio-temporal gait measurement system using labview vision. *JSIR Vol.69(08)* (2010), 600–605. 18, 195

[61] KUNZE, K., BARRY, M., HEINZ, E. A., LUKOWICZ, P., MAJOE, D., AND GUTKNECHT, J. Towards recognizing tai chi an initial experiment using wearable sensors. In *Heinz1, Paul Lukowicz, Dennis Majoe, Jurg Gutknecht; Institute for Computer Systems and Networks UMIT* (2006). 36, 39

[62] KWAPISZ, J. R., WEISS, G. M., AND MOORE, S. A. Activity recognition using cell phone accelerometers. *Human Factors* (2010), 1018. Available from: `http://storm.cis.fordham.edu/~gweiss/papers/sensorKDD-2010.pdf`. 35, 36, 131, 133, 148

[63] KYRIAZIS, V., AND RIGAS, C. Software for temporal gait data analysis. *Computer Methods and Programs in Biomedicine 67*, 3 (2002), 225 – 229. Available from: `http://www.sciencedirect.com/science/article/pii/S0169260701001523`. 18

[64] LAERHOVEN, K. V., AND CAKMAKCI, O. What shall we teach our pants? In *Proceedings of the 4th IEEE International Symposium on Wearable Computers* (Washington, DC, USA, 2000), ISWC '00, IEEE Computer Society, pp. 77–. Available from: `http://portal.acm.org/citation.cfm?id=851037.856531`. 37, 134

[65] LAERHOVEN, K. V., AND GELLERSEN, H.-W. Spine versus porcupine: A study in distributed wearable activity recognition. In *Proceedings of the Eighth International Symposium on Wearable Computers* (Washington, DC, USA, 2004), ISWC '04, IEEE Computer Society, pp. 142–149. Available from: `http://dx.doi.org/10.1109/ISWC.2004.40`. 36, 38

[66] LARSEN, P., SIMONSEN, E., AND LYNNERUP, N. Gait analysis in forensic medicine. *J Forensic Sci* (2008). 18, 133, 134, 137

[67] LARSEN, P. K., SIMONSEN, E. B., AND LYNNERUP, N. Gait analysis in forensic medicine. *Journal of Forensic Sciences 53*, 5 (2008), 1149–1153. 17, 195

[68] LEE, C.-Y., AND LEE, J.-J. Estimation of walking behavior using accelerometers in gait rehabilitation. *International Journal of Human-friendly Welfare Robotic Systems 3*, 32–36. 22, 78, 132, 134

[69] LEE, S. W., AND MASE, K. Activity and Location Recognition Using Wearable Sensors. *IEEE Pervasive Computing 1*, 3 (July 2002), 24–32. Available from: `http://dx.doi.org/10.1109/MPRV.2002.1037719`. 40

[70] LESTER, J., CHOUDHURY, T., AND BORRIELLO, G. A Practical Approach to Recognizing Physical Activities. In *Pervasive Computing*, K. Fishkin, B. Schiele, P. Nixon, and A. Quigley, Eds., vol. 3968 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, Berlin, Heidelberg, 2006, ch. 1, pp. 1–16. Available from: `http://dx.doi.org/10.1007/11748625_1`. 35, 131, 134, 148

[71] LESTER, J., CHOUDHURY, T., KERN, N., BORRIELLO, G., AND HANNAFORD, B. A hybrid discriminative/generative approach for modeling human activities. In *In Proc. of the International Joint Conference on Artificial Intelligence (IJCAI)* (2005), pp. 766–772. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.77.5776`. 35

[72] LIU, B. *Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data (Data-Centric Systems and Applications)*, 1st ed. 2007. corr. 2nd printing ed. Springer, Jan. 2009. Available from: `http://www.amazon.com/exec/obidos/redirect?tag=citeulike07-20&path=ASIN/3540378812`. ix, xi, 39, 134, 135

[73] LOGAN, B., HEALEY, J., PHILIPOSE, M., TAPIA, E., AND INTILLE, S. A Long-Term Evaluation of Sensing Modalities for Activity Recognition. In *UbiComp 2007: Ubiquitous Computing*, J. Krumm, G. D. Abowd, A. Seneviratne, and T. Strang, Eds., vol. 4717 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg, Berlin, Heidelberg, 2007, ch. 28, pp. 483–500. Available from: `http://dx.doi.org/10.1007/978-3-540-74853-3_28`. 36

[74] LOMBRISER, C., BHARATULA, N. B., ROGGEN, D., AND TRÖSTER, G. On-body activity recognition in a dynamic sensor network. In *Proceedings of the ICST 2nd international conference on Body area networks* (ICST, Brussels, Belgium, Belgium, 2007), BodyNets '07, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), pp. 17:1–17:6. Available from: `http://portal.acm.org/citation.cfm?id=1460232.1460249`. ix, 37, 38, 134

[75] LONG, X., YIN, B., AND AARTS, R. Single-accelerometer-based daily physical activity classification. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE* (2009), pp. 6107 –6110. 35, 40, 131, 137, 148

[76] MAHAJAN, D., KWATRA, N., JAIN, S., KALRA, P., AND BANERJEE, S. A framework for Activity Recognition and Detection of Unusual Activities. In *Proc. Indian Conference on Computer Vision, Graphics and Image Processing* (December 2004). 40, 135

[77] MANNINI, A., AND SABATINI, A. M. Machine learning methods for classifying human physical activity from on-body accelerometers. *Sensors 10*, 2 (2010), 1154–1175. Available from: `http://www.mdpi.com/1424-8220/10/2/1154`. 38

[78] MANTYJARVI, J., HIMBERG, J., AND SEPPÄNEN, T. Recognizing human motion with multiple acceleration sensors. vol. 2. Available from: `http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=973004`. 20, 25, 29, 36, 40

[79] MATHIE, M., LOVELL, N., COSTER, A., AND CELLER, B. Determining activity using a triaxial accelerometer. In *Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES*

Conference, 2002. Proceedings of the Second Joint (2002), vol. 3, pp. 2481 – 2482 vol.3. 35, 131, 148

[80] MAURER, U., SMAILAGIC, A., SIEWIOREK, D. P., AND DEISHER, M. Activity recognition and monitoring using multiple sensors on different body positions. In *Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks* (Washington, DC, USA, 2006), IEEE Computer Society, pp. 113–116. Available from: `http://portal.acm.org/citation.cfm?id=1121990.1122269`. 36, 37

[81] MAURER, U., SMAILAGIC, A., SIEWIOREK, D. P., AND DEISHER, M. Activity recognition and monitoring using multiple sensors on different body positions. In *Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks* (Washington, DC, USA, 2006), IEEE Computer Society, pp. 113–116. Available from: `http://portal.acm.org/citation.cfm?id=1121990.1122269`. 40, 137

[82] MIDDLETON, L., BUSS, A. A., BAZIN, A., AND NIXON, M. S. A floor sensor system for gait recognition. In *Proceedings of the Fourth IEEE Workshop on Automatic Identification Advanced Technologies* (Washington, DC, USA, 2005), IEEE Computer Society, pp. 171–176. Available from: `http://portal.acm.org/citation.cfm?id=1104713.1104745`. 18, 132

[83] MINNEN, D., STARNER, T., ESSA, M., AND ISBELL, C. Discovering Characteristic Actions from On-Body Sensor Data. *Wearable Computers, 2006 10th IEEE International Symposium on* (2006), 11–18. Available from: `http://dx.doi.org/10.1109/ISWC.2006.286337`. 40, 135

[84] MJAALAND, B. B. Gait mimicking - attack resistance testing of gait authentication systems. Master's thesis, Norwegian University of Science and Technology, 2009. ix, 19, 20, 25, 26, 27, 28, 29, 32

[85] MORI, T., SUEMASU, Y., NOGUCHI, H., AND SATO, T. Multiple people tracking by integrating distributed floor pressure sensors and rfid system. In *Systems, Man and Cybernetics, 2004 IEEE International Conference on* (oct. 2004), vol. 6, pp. 5271 – 5278 vol.6. 18

[86] MORRIS, S. J. *A shoe-integrated sensor system for wireless gait analysis and real-time therapeutic feedback*. Ph.D. thesis, Division of Health Sciences and Technology, Harvard University-MIT, 2004. 33, 82

[87] MOSTAYED, A., KIM, S., MAZUMDER, M. M. G., AND PARK, S. J. Foot step based person identification using histogram similarity and wavelet decomposition. In *ISA '08: Proceedings of the 2008 International Conference on Information Security and Assurance (isa 2008)* (Washington, DC, USA, 2008), IEEE Computer Society, pp. 307–311. 22, 24, 31, 78, 80

[88] NAEEM, U., BIGHAM, J., AND WANG, J. Recognising activities of daily life using hierarchical plans. In *Proceedings of the 2nd European conference on Smart sensing and context* (Berlin, Heidelberg, 2007), EuroSSC'07, Springer-Verlag, pp. 175–189. Available from: `http://portal.acm.org/citation.cfm?id=1775377.1775391`. 35

[89] NGUYEN, A., MOORE, D., AND MCCOWAN, I. Unsupervised clustering of free-living human activities using ambulatory accelerometry. *Conf Proc IEEE Eng Med Biol Soc 2007* (2007), 4895–8. Available from: `http://www.biomedsearch.com/nih/Unsupervised-clustering-free-living-human/18003103.html`. 40, 135

[90] Nickel, C., Brandt, H., and Busch, C. Benchmarking the performance of svms and hmms for accelerometer-based biometric gait recognition. In *Signal Processing and Information Technology (ISSPIT), 2011 IEEE International Symposium on* (dec. 2011), pp. 281 –286. 20, 33

[91] Nixon, M. S., Carter, J. N., Grant, M. G., Gordon, L. G., and Hayfron-Acquah, J. B. Automatic recognition by gait: progress and prospects. *Sensor Review 23*, 4 (2003), 323–331. Available from: http://eprints.ecs.soton.ac.uk/8441/. ix, 17

[92] Nixon, M. S., Carter, J. N., Shutler, J., and Grant, M. New advances in automatic gait recognition. *Elsevier Information Security Technical Report 7*, 4 (2002), 23–35. Available from: http://eprints.ecs.soton.ac.uk/7904/. 35, 36, 131, 132, 148

[93] Niyogi, S., and Adelson, E. Analyzing and recognizing walking figures in xyt. In *CVPR '94.* (jun 1994), pp. 469 –474. 18

[94] Nowozin, S., Bakir, G., and Tsuda, K. Discriminative subsequence mining for action classification. In *Computer Vision, 2007. ICCV 2007. IEEE 11th International Conference on* (2007), pp. 1 –8. 36

[95] Okumura, F., Kubota, A., Hatori, Y., Matsuo, K., Hashimoto, M., and Koike, A. A study on biometric authentication based on arm sweep action with acceleration sensor. In *Intelligent Signal Processing and Communications, 2006. ISPACS '06. International Symposium on* (dec. 2006), pp. 219 –222. 41

[96] Oliver, N., and Flores-Mangas, F. Healthgear: A real-time wearable system for monitoring and analyzing physiological signals. *Wearable and Implantable Body Sensor Networks, International Workshop on 0* (2006), 61–64. 36

[97] Orr, R. J., and Abowd, G. D. The smart floor: a mechanism for natural user identification and tracking. In *CHI '00 extended abstracts on Human factors in computing systems* (New York, NY, USA, 2000), CHI EA '00, ACM, pp. 275–276. Available from: http://doi.acm.org/10.1145/633292.633453. 18

[98] Patterson, D., Fox, D., Kautz, H., and Philipose, M. Fine-grained activity recognition by aggregating abstract object usage. In *Wearable Computers, 2005. Proceedings. Ninth IEEE International Symposium on* (2005), pp. 44 – 51. 36, 39

[99] Patterson, D. J., Liao, L., Gajos, K., Collier, M., Livic, N., Olson, K., Wang, S., Fox, D., and Kautz, H. Opportunity Knocks: A System to Provide Cognitive Assistance with Transportation Services. 2004, pp. 433–450. Available from: http://www.springerlink.com/content/xh22c1262bny1fly. 40, 135

[100] Philipose, M., Fishkin, K., Perkowitz, M., Patterson, D., Fox, D., Kautz, H., and Hahnel, D. Inferring activities from interactions with objects. *Pervasive Computing, IEEE 3*, 4 (2004), 50 – 57. 35, 36

[101] Pirttikangas, S., Fujinami, K., and Nakajima, T. Feature selection and activity recognition from wearable sensors. In *UCS* (2006), pp. 516–527. Available from: http://www.springerlink.com/content/gw3x126p42786532. 36, 132, 134

[102] Randell, C., and Muller, H. Context awareness by analysing accelerometer data. In *Digest of Papers. Fourth International Symposium on Wearable Computers* (Los Alamitos, CA, USA, 2000), vol. 0, IEEE Comput. Soc, pp. 175–176. Available from: http://dx.doi.org/10.1109/ISWC.2000.888488. 36, 133

[103] Ravi, N., Dandekar, N., Mysore, P., and Littman, M. L. Activity Recognition from Accelerometer Data. *American Association for Artificial Intelligence* (2005). Available from: `http://paul.rutgers.edu/~{}nravi/accelerometer.pdf`. 36, 39

[104] Reutemann, D. S. P. *WEKA Experimenter Tutorial for Version 3-5-5*. David Scuse and University of Waikato, January 26 2007. 33

[105] Rong, L., Jianzhong, Z., Ming, L., and Xiang, H. Identification of individual walking patterns using gait acceleration. *In 1st International Conference in Bioinformatics and Biomedical Engineering* (2005), 543–546. 22, 40, 77, 78, 132, 134, 135

[106] Rong, L., Jianzhong, Z., Ming, L., and Xiangfeng, H. A wearable acceleration sensor system for gait recognition. In *Industrial Electronics and Applications, 2007. ICIEA 2007* (2007), pp. 2654–2659. 20, 22, 30, 33, 77, 78, 80, 82

[107] Sazonov, E., Bumpus, T., Zeigler, S., and Marocco, S. Classification of plantar pressure and heel acceleration patterns using neural networks. In *International Joint Conference on Neural Networks, IJCNN '* (2005), IEEE. 22, 33, 78, 134, 135

[108] Sekine, M., Tamura, T., Akay, M., Togawa, T., and Fukui, Y. Analysis of acceleration signals using wavelet transform. *Methods Inf Med 39*, 2 (2000), 183–5. Available from: `http://www.biomedsearch.com/nih/Analysis-acceleration-signals-using-wavelet/10892260.html`. 36, 133

[109] SensorWiki. Accelerometer. Available from: `http://sensorwiki.org/doku.php/sensors/accelerometer`. 21

[110] Shabeer, H. A., and Suganthi, P. Mobile phones security using biometrics. In *Proceedings of the International Conference on Computational Intelligence and Multimedia Applications (ICCIMA 2007) - Volume 04* (Washington, DC, USA, 2007), ICCIMA '07, IEEE Computer Society, pp. 270–274. Available from: `http://dx.doi.org/10.1109/ICCIMA.2007.288`. 41

[111] Shakespeare, W., and Tinker, C. *The Tempest*. The Yale Shakespeare. Yale University Press, 1922. Available from: `http://books.google.no/books?id=_fEVAAAAYAAJ`. 9

[112] Sprager, S., and Zazula, D. Gait identification using cumulants of accelerometer data. In *SENSIG'09/VIS'09/MATERIALS'09: Proceedings of the 2nd WSEAS International Conference on Sensors, and Signals and Visualization, Imaging and Simulation and Materials Science* (Stevens Point, Wisconsin, USA, 2009), World Scientific and Engineering Academy and Society (WSEAS), pp. 94–99. 22, 30, 33, 77, 78, 79, 80, 81

[113] Stikic, M., Huynh, T., Van Laerhoven, K., and Schiele, B. ADL Recognition Based on the Combination of RFID and Accelerometer Sensing. In *Proceedings of the 2nd International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health 2008)* (Tampere, Finland, January 2008), IEEE Xplore, IEEE Xplore, p. 258–263. 35, 36, 38

[114] Stikic, M., Van Laerhoven, K., and Schiele, B. Exploring semi-supervised and active learning for activity recognition. In *Proceedings of the 12th International Symposium on Wearable Computers (ISWC 2008)* (Pittsburgh, USA, September 2008), IEEE Press, IEEE Press, pp. 81–90. 38

[115] Streitz. Norbert, N. P. The disappearing computer. *Commun. ACM* (2005), 32–35. Available from: `http://dx.doi.org/10.1145/1047671.1047700`. 35, 83, 131

[116] TAPIA, E. M., INTILLE, S. S., AND LARSON, K. Activity Recognition in the Home Using Simple and Ubiquitous Sensors. In *Pervasive Computing*, A. Ferscha and F. Mattern, Eds., vol. 3001 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, 2004, pp. 158–175–175. Available from: `http://dx.doi.org/10.1007/978-3-540-24646-6_10`. 35

[117] TIMESONLINE. Aiming to catch criminals red-footed. Available from: `http://business.timesonline.co.uk/tol/business/law/article685365.ece`. 18, 35, 131, 132, 134, 135

[118] UNION, I. T. Biometrics and Standards. *ITU-T Technology Watch Report* (2009). ix, 15, 16

[119] VAN LAERHOVEN, K., AND CAKMAKCI, O. What shall we teach our pants? In *Wearable Computers, 2000. The Fourth International Symposium on* (2000), pp. 77 –83. 36, 39

[120] VILDJIOUNAITE, E., MÄKELÄ, S.-M., LINDHOLM, M., RIIHIMÄKI, R., KYLLÖNEN, V., MÄNTYJÄRVI, J., AND AILISTO, H. Unobtrusive multimodal biometrics for ensuring privacy and information security with personal devices. In *Pervasive* (2006), pp. 187–201. 33, 82

[121] WANG, J., LI, Y., LIANG, P., ZHANG, G., AND AO, X. An effective multi-biometrics solution for embedded device. In *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on* (oct. 2009), pp. 917 –922. 41

[122] WANG, L., NING, H., TAN, T., AND HU, W. Fusion of static and dynamic body biometrics for gait recognition. 149–158. 18

[123] WANG, N., AMBIKAIRAJAH, E., LOVELL, N. H., AND CELLER, B. G. Accelerometry based classification of walking patterns using time-frequency analysis. *Conf Proc IEEE Eng Med Biol Soc 2007* (2007), 4899–902. Available from: `http://www.biomedsearch.com/nih/Accelerometry-based-classification-walking-patterns/18003104.html`. 35, 131, 148

[124] WANG, S., PENTNEY, W., POPESCU, A.-M., CHOUDHURY, T., AND PHILIPOSE, M. Common Sense Based Joint Training of Human Activity Recognizers. In *In: Proceedings of the 20th International Joint Conference on Artificial Intelligence* (2007), pp. 2237–2242. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.61.5347`. 35, 38

[125] WANG, X., LI, Y., AND QIAO, F. Gait authentication based on multi-criterion model of acceleration features. In *Modelling, Identification and Control (ICMIC), The 2010 International Conference on* (2010), pp. 664–669. 20

[126] WARD, J. A., LUKOWICZ, P., AND TRÖSTER, G. Gesture spotting using wrist worn microphone and 3-axis accelerometer. In *sOc-EUSAI '05: Proceedings of the 2005 joint conference on Smart objects and ambient intelligence* (New York, NY, USA, 2005), ACM Press, pp. 99–104. Available from: `http://dx.doi.org/10.1145/1107548.1107578`. 36, 133, 134

[127] YANG, J., WANG, S., CHEN, N., CHEN, X., AND SHI, P. Wearable accelerometer based extendable activity recognition system. In *Robotics and Automation (ICRA), 2010 IEEE International Conference on* (May 2010), pp. 3641 –3647. 35, 131

[128] ZHU, C., AND SHENG, W. Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on PP*, 99 (2011), 1 –5. 36, 132

Chapter 3

Contributions and Summary

3.1 Paper contributions

This section presents a summary of the contributions of each of the papers included in chapters 4 - 11.

3.1.1 Accelerometer-Based Gait Analysis, A Survey [1]

This paper is on the taxonomy of person recognition approaches based on gait. It takes a technological perspective on how biometric gait recognition can be categorized into three approaches, namely the Machine Vision based, Floor Sensor based and Wearable Sensor based. It covers the current state of art of accelerometer based gait recognition which is a sub-category of wearable sensor based gait recognition. It gives a complete literature study describing the major modules; experiments, data acquisition, data analysis and comparison of different gait recognition systems.

The main of accelerometer gait recognition is that it provides unobtrusive user authentication and identification. There are many factors that can influence the accuracy of such a system. These factors have to be taken into consideration when developing a robust system. Therefore, accelerometer based gait biometrics is still not mature and additional research needs to be performed. Since wearable based gait biometrics was first investigated in 2005, has there been an increasing interest within this topic. However, no public database has been created within this research field which makes the comparison of the performance results in the various works more difficult to compare.

3.1.2 Towards Continuous Authentication Based on Gait Using Wearable Motion Recording Sensors [6]

In this paper we developed a framework for continuous evaluations of the genuineness of a person through accelerometer based gait recognition.

Usually all systems conduct some kind of user authentication before granting access to objects or services. In addition, individuals pass through authentication mechanisms multiple times in their everyday activity, e.g. for entering a house you have to retain the correct key to open the door or to use a laptop you need to know its password. These authentications are one-time or static, which in general terms means once the user's identity is verified to be correct the authentication lasts persistently. Nevertheless, some systems have the need of ensuring the identity of the user during the full session. This then requires verification of user identity continuously. One of the important necessities for continuous authentication is that the approach should be unobtrusive and appropriate in usage. If this is not fulfilled the users are not going to accept continuous authentication. Hence not every authentication method is appropriate for continuous authentication even if they offer higher security.

We discuss the pros and cons of gait biometrics in the perspective of continuous authentication. Gait is captured using wearable motion recording sensors (semi-)attached to the individual's body. One of the advantages of using wearable-sensor based gait recognition in continuous authentication is its unobtrusiveness. Whenever a user generates gait information, his/her identity is verified indirectly in the background without disrupting the person from his/her normal activity. The framework we propose prolongs the traditional static authentication to account for continuous (re-)verification of the user's identity. The proposed continuous authentication framework can effortlessly be attuned for other biometric modalities which are appropriate for continuous authentication.

Guaranteeing the correct identity of a user throughout a full session is essential. In static biometric user authentication the authentication mechanism will make a decision about the correctness of the claimed user identity directly after the user has inputted his biometric feature. This decision is either accepting or rejecting this user, resulting in either access or not to the specific system. System performance is measured in terms of errors that are made by making the decision, i.e. in terms of FMR and FNMR.

For a continuous biometric user authentication mechanism it is assumed that the identity of a user has been verified by a static authentication mechanism. A biometric continuous authentication mechanism will only reject individuals if there is doubt that the current user is not the genuine one, whose identity was verified through the static authentication mechanism. In order to be able to measure the genuineness of a user we introduced trust levels and a way to adjust the trust level, based on newly defined penalty and reward functions. The performance of a continuous authentication system is measured in terms of how long it takes before an impostor is detected and locked out by the system.

3.1.3 Unobtrusive User-Authentication on Mobile Phones using Biometric Gait Recognition [7]

This research work demonstrates how one has the ability to use commercial mobile phones equipped with accelerometers to carry out biometric gait recognition. This paper has further been given the *best paper award* for its novelty and uniqueness. To the best of our knowledge, this is the first time that data, collected by accelerometers in a standard mobile phone, was used for biometric gait recognition.

The paper introduces how a gait recognition system is implemented into a mobile phone. The system performs an unobtrusive operation which gives a high user friendliness. We propose gait recognition as a protection mechanism to improve the device security. Unlike previous work on wearable-based gait recognition, which was dedicated by using high-grade accelerometers, this paper reports the performance when the data is collected with a commercially available mobile device containing low-grade accelerometers. To be more exact, the used mobile device is the Google G1 phone containing the AK8976A embedded accelerometer sensor. The mobile device was placed at the hip off each volunteer to collect gait data. Several processing steps such as preprocessing, cycle detection and recognition-analysis were applied to the acceleration signal. The raw data retrieved from the mobile phone was processed to create robust templates for all subjects. The feature extraction method used was the *average cycle method* using *Dynamic Time Warping* for comparison. The analysis was applied to the data of 51 volunteers. Each volunteer provided gait acceleration data in two sessions and N data samples per session. The achieved EER of 20.1% is approximately 50% higher than the EER achieved with a similar method using a dedicated accelerometer with a twice as high sampling rate. This obtained EER indicates that biometric gait recognition can be run on mobile phones but it is not yet ready for practical use.

3.1.4 Improved Cycle Detection for Accelerometer Based Gait Authentication [5]

In this paper an improved biometric gait recognition approach is presented with a stable cycle detection mechanism and new comparison algorithm. Compared to the previous work on wearable gait recognition [7], which was based of simple average cycling methods, this paper introduces a new approach which has a large effect on the performance. The main purpose of this paper was to look at the performance by developing new algorithms and not the use of mobile phone sensor for collecting data. All of the published studies on gait recognition using acceleration data were only slightly aware of fulfilling these issues at the very same time: 1) An stable cycle detection mechanism and 2) A well performing comparison algorithm.

The new, simple and well performing gait recognition approach was proposed to improve over the performance of the average cycle method. The proposed algorithm developed performs automated cycle-detection (which was given the name *neighbour search* algorithm), which works in finding the best and most optimal distance score from two feature vectors with the use of cross comparison and the *cyclic rotation metric* (CRM) as a distance metric.

The proposed feature extraction method was adapted and applied to data from 60 volunteers. We obtained a resulting EER of 5.7%, which is low compared to other research, specially when taking into account the number of participants and the number of data samples per participant. Even though this paper had fewer participants than some of the other databases collected over time, we did have more data samples per participant, almost up to twice the number of gait sequences.

3.1.5 Scenario Test of Accelerometer-Based Biometric Gait Recognition [8]

The contribution of this paper is to develop methods for accelerometer-based gait recognition, which are robust, stable and fast enough to be used for authentication on mobile devices. To show how far we are in reaching this goal we developed a new cycle extraction method, implemented an application for Android phones and conducted a scenario test. We evaluated two different methods, which apply the same cycle extraction technique but use different comparison methods. In total 48 subjects participated in the scenario test. After enrollment they walked for about 15 minutes on a predefined route. To get a realistic scenario this route included for example climbing of stairs, opening doors and walking around corners. About every 30 seconds the subject stopped and the authentication was started.

This paper introduces the new cycle extraction method and shows the Detection Error Trade-Off-curves, error rates by route-section as well as the computation times for enrollment and authentication on a Motorola Milestone phone.

The new cycle extraction method, which was based on salience vectors, was combined with two different comparison methods. On two different days each of the 48 participants walked for about 15 minutes on a predefined cyclic route which included 9 stopping points where the authentication data was stored. In contrast to previously conducted experiments, this route did contain corners, stairs and doors. Despite these obstacles, we obtained an equal error rate of 21.7% for the module using cyclic rotation metric as a distance and of 28.0% for the module using majority voting. Although these results are not as good as the results stated in other related papers, are the circumstance in the experiment closer to reality. One reason is the more realistic data collection (not only flat floor) the other reason is that the stated EERs are obtained when comparing probe data of one day to reference data of a second day. We showed that this time difference has a great impact on the recognition rates, which is seldom considered in literature.

Furthermore we included the use of the modules for continuous authentication. So far, the authentication is started only once when the user wants to use his phone again and switches off the screen saver. As extracting cycles from 30 seconds of data and doing the comparison with the reference template takes about 30 seconds at the moment, this is not user-friendly. Alternating phases where data is collected with those where the cycle extraction and comparison is done and always storing the most current authentication result will improve this situation as only that the latest authentication result has to be obtained.

Adding this enhancement, the CRM-module can be used as a supplement to PIN authentication on mobile phones.

3.1.6 Towards an Automatic Gait Recognition System using Activity Recognition (Wearable Based) [3]

This paper describes a system where the combination of activity recognition and gait recognition is used to create a continuous and automatic authentication system on mobile devices. Such a combined system has not been published before. By using activity recognition as an important element for the authentication process we proposed an automatic gait recognition system to be used for continuous authentication. We proposed a solution on how activity recognition would reduce the challenges of gait recognition by identifying the activities of a person continuously and automatically. Activity recognition would not only make it possible to authenticate the user in different daily activities like slow walking, normal walking, fast walking or even running, but also helps in avoiding deep analysis of the accelerometer data when the user is in passive state like sitting or standing still. Activity recognition is one of the key factors in gait recognition and an interesting challenge which would beneficial to the data security area.

Activity and gait recognition has been studied separately in the recent years, but the interest has increased lately because of the fact that mobile phones today include embedded accelerometers. The recognition accuracy for activity recognition has shown great results, which means that it can be useful for an automatic gait recognition system.

3.1.7 Activity Recognition Using Smart Phones [2]

In this research work we analyze activity recognition to ensure that only the authorized user can access the data in a mobile phone.

Recent gait recognition research focuses on manual extraction of walking activities from the accelerometer signal. In this paper we do performance analysis of activity recognition that would reduce the disadvantages of gait recognition by identifying the activities of a person continuously and automatically.

A novel and simple authentication system has been analyzed and proposed. The proposed system in using activity recognition for gait recognition is applied to data from 45 volunteers. Activity recognition is a relatively new area of study and over the last decade has become an interesting research field due to its application in many areas. In our experiment we included stable walking activities like normal, fast and slow.

In the performance analysis we retrieved several results using different classifiers. We performed two different main test, namely a personal and global cross validation test. In the first test we performed a cross validation for individual-based activity recognition. This means that we look separately at each users's activity performance with a retrieved accuracy of 96.08%. In the second test we merged all data together from all sessions of all subjects. In contrast to the personal cross validation, these results shows how similar or different each subjects fast, slow, and normal walk is from each other for all users with a highest accuracy of 79.62%.

3.1.8 Gait and Activity Recognition using Commercial Phones [4]

In this paper we analyzed the performance of a system that combines both activity and gait recognition. The system is implemented on an off-the-shelf smart phone, the Samsung Nexus S. The activity recognition feature allows users to enroll various activities, such as running, walking, or standing. This is done by enrolling these activities as reference templates into the smart phone. When the activity recognition identifies a walking activity, then the gait recognition system can use this information to identify the correct user. The implemented gait feature extraction learns particular characteristics of how people walk, allowing the phone to identify its user. The gait recognition is further dependent on the activity recognition, since the mobile phone should identify activities before verifying the user with gait recognition.

The best equal error rate achieved was 5.7 %. This error rate is the lowest error rate retrieved within gait recognition into a smartphone. Biometric gait recognition in smart phones has become a realistic approach for smartphone users and to protect its information from unauthorized access.

3.2 Accomplishments and Future work

User recognition based on gait using mobile devices (sensor based) is a very recent methodology compared to the other gait approaches, namely the machine video based and floor sensor based, or other conventional biometric modalities. To summarize the accomplished work, the list of the research questions and issues that needs to be resolved are given below:

1. **A state-of-the-art regarding wearable based gait recognition:** This research question has been addressed in paper [1]. It gives a state-of-the-art about gait recognition in general describing the three approaches; (1) Machine Vision, (2) Floor Sensor and (3) Wearable Sensor Based technologies. In addition, it goes into further details describing the several methodologies on how gait analysis is performed. Since its publication research has progressed and, like any state of the art article, it need regular updating.

2. **To develop a gait recognition system on mobile devices:** This research question has been addressed in papers [4, 5, 7, 8]. Novel cycle feature extractors and comparators have been developed deviating from the existing ones, i.e. the average cycle method and the step detection method. An effective cycle detection mechanism has been proposed and tested out on several datasets. For the comparison, 3 innovative methods were created, namely the Cyclic Rotation Metric (CRM), Cross-DTW metric (CDM) and Majority Voting (MV). All of the three methods incorporate the Dynamic Time Warping (DTW). Four gait datasets were created where a phone was used to collect data from each subject. A smartphone gait recognition application has been developed to process the gait data on the phone.

   To gain a stable gait recognition system several work needs to be performed. The application needs to be optimized in calculation time and power usage. Better methods are calculation intensive, so for the moment only simple methods works fast and elaborate methods do not work real-time.

3. **To develop an activity identification system on mobile devices:** This research question has been addressed in [2, 3, 4] These papers propose a model on how activity recognition can be combined with gait recognition. Activity identification is an important step to detect daily activities. The work deals with the detection of three different walking speeds , i.e. normal, fast and slow walking. It is shown that the recognition performance of different speed types are dissimilar, in particular the performance for slow walking is lower than for fast and normal walking. Several machine learning algorithms have been applied to the developed datasets and the performance evaluation was done in the WEKA framework which has retrieved highly acceptable results.

   In the future more daily activities should be identified in the analysis. Also a more clear distinction between cyclic and non-cyclic activities should be implemented. The analysis so far only was done on discrete datasets that contained only one activity and a continuous change from one activity to another has not yet been investigated.

4. **Continuous authentication on mobile devices:** This research question has been addressed in [6].The work proposes a model for how continuous authentication can ensure that the legitimate user is authorized to use the phone at any time, while an illegitimate

user is detected as soon as possible. A framework on how such a system can be implemented into a phone is described. It introduced confidence interval, trust level, and how pyramided authentication works. The paper describes a model for continuous authentication, but has not been implemented on a smartphone so far.

Since this is a prototype, it is however a gap that needs to be working with and fulfilled.

Future work considerations in this field of research are still there. In the following we outline possible directions that could be a natural extension of the work presented in this thesis:

Performance Evaluation The performance of mobile-based gait biometrics is less than the performance of robust and strong biometrics like vein-, finger- or iris-recognition. Since accelerometer data conducts signals as output based on time, it is most obvious that one takes a deep look into digital signal processing (DSP). Few examples such as the FFT, DWT, cross-correlation have been tried already, but the information retrieved has not been so specific. Furthermore, the average cycle method is not a fully automated gait recognition method and therefore DSP could be used for the same purpose making the process automatic and more reliable. Multi-modal biometric are currently considered a major-topic in biometric systems and might also be useful within sensor based gait recognition. Mobile devices today have several types of built-in sensors (e.g. gyroscopes, magnetic field sensors etc.) which eventually outputs some data that might be combined with each other. Fusion of the three directions (x, y, z) should be considered that might have a great impact improving authentication performances.

Fast/efficient implementations The newer smartphones are produced with even better processors than ever before. One of the advantages is that they can then run a biometric gait algorithm even faster. This might help with reducing the algorithm performance time saving several (milli)seconds. However, still algorithm software optimization is needed for gait algorithms to make some aspects of it work more efficiently or to use fewer resources. The enrollment, identification or verification algorithm execution time is currently still an issue and must be dealt with. It might not be appropriate to use a smartphone application that takes longer time than the user's patience.

Continuous Authentication (CA) In gait biometric user authentication, the authentication mechanism will make a decision about the correctness of the claimed user identity directly after the user has walked. This decision is either accepting or rejecting this user, resulting in either access to the particular system or not. A difference for a continuous biometric user authentication mechanism is that the user is by default accepted due to the fact that his or her identity has been verified by a static authentication mechanism. A biometric continuous authentication mechanism will therefore only reject users if they have shown not to be the genuine user. In order to be able to measure the genuineness of the user we suggest, in future work, to implement trust levels and a way to adjust the trust level based on the difference between the current walking and the template. The performance of a continuous authentication system is measured in terms of how long it takes before an impostor is detected and locked out by the system. These function should be implemented as an application in mobile phones and to measure the exact performances, i.e. the time it takes before impostor users are recognized as such by the CA mechanism and are locked out of the system.

Template Protection The characteristic gait of a subject is recorded using accelerometers in a mobile device. From this data biometric feature vectors can be extracted and stored as reference data on the device. Only if the user is not recognized by his walk an active authentication via PIN is necessary. As the number of attacks on mobile devices increases it cannot be assumed that the data stored on the device is under constant control of the subject. Therefore, template protection techniques should be applied to secure stored biometric data. No specific template protection methods for gait recognition have been researched so far.

Mimicking Although this thesis did not research on the mimicking issue on gait, it is suggested as further research. When trying to mimick another person, it is useful to verify whether these volunteers are sheeps (people whose gait is easy to mimic) or wolves (people who are good at mimicking other peoples gait). The bottom line question is whether it is possible to learn to walk like someone else. If this would turn out to be simple, it will have a severe effect on the potential of gait as an authentication mechanism in the future. Mimicking has only been performed with the use of external dedicated sensors and not with a mobile device. It needs to be investigated if the results for mimicking with mobile devices are the same as for dedicated sensors.

Bio-mechanics The way you walk is a complex biological process that involves nervous and musculo-skeletal systems. To get an understanding of gaits inherit potentials and limitations for security applications, a (long-term) multi-disciplinary approach that combines knowledge from various domains such as medicine, bio-mechanics, physics, IT, etc. might be considered. In this manner, one is able to understand the information retrieved in technical and practical means from the output that is given by the sensors inside the mobile devices.

Public database Unlike video-based gait recognition, the mobile-based lacks a large publicly available database. The creation of such a large wearable sensor-based database using mobile devices will in the future facilitate the development in the direction of the wearable sensor-based approach. It will further also give the possibility of direct comparisons of various developed algorithms. Newly created databases should include various external and possibly internal factors that can influence gait biometrics. External factors are mostly impose challenges to the recognition approach (or algorithm). For example, outdoor/indoor environments (e.g. sunny, rainy days), clothes (e.g. skirts in WS-based category), walking surface conditions (e.g. hard/soft, dry/wet grass/concrete, level/stairs, etc.), shoe types (e.g. mountain boots, sandals), object carrying (e.g. backpack, briefcase), etc. Internal factors cause changes of the natural gait due to sickness (e.g. foot injury, lower limb disorder, Parkinson disease etc.) or other physiological changes in body due to aging, drunkenness, pregnancy, gaining or losing weight, etc.

3.3 Bibliography

[1] DERAWI, M. O. Accelerometer-based gait analysis, a survey. In *Norwegian Information Security Conference* (Gjøvik, Norway, 2010), NISK '10, Tapir, pp. 33–44. 53, 57

[2] DERAWI, M. O., BAJRAMI, G., AND BOURS, P. Gait and activity recognition using smart phones. *International Conference on Pervasive Computing, Signal Processing and Applications* (2011). 56, 57, 225

[3] DERAWI, M. O., BAJRAMI, G., AND BOURS, P. Towards an automatic gait recognition system using activity recognition (wearable based). *International Conference on Security and Communication Networks (IWSCN)* (2011). 56, 57

[4] DERAWI, M. O., AND BOURS, P. Gait and activity recognition using commercial phones. *Submitted to the 5th International Conference on Biometrics: Theory, Applications and Systems (BTAS)* (2012). 56, 57, 225

[5] DERAWI, M. O., BOURS, P., AND HOLIEN, K. Improved cycle detection for accelerometer based gait authentication. In *International Conference on Intelligent Information Hiding and Multimedia Signal Processing - Special Session on Advances in Biometrics* (2010). 25, 27, 29, 54, 57, 225, 227

[6] DERAWI, M. O., GAFUROV, D., AND BOURS, P. Towards continuous authentication based on gait using wearable motion recording sensors. *In Continuous Authentication Using Biometrics: Data, Models, and Metrics. IGI Global (ISBN: 9781613501290)* (2012). 53, 57

[7] DERAWI, M. O., NICKEL, C., BOURS, P., AND BUSCH, C. Unobtrusive user-authentication on mobile phones using biometric gait recognition. *International Conference on Intelligent Information Hiding and Multimedia Signal Processing* (2010), 306–311. 54, 57, 225

[8] NICKEL, C., DERAWI, M., BOURS, P., AND BUSCH, C. Scenario test for accelerometer-based biometric gait recognition. In *International Conference on Security and Communication Networks (IWSCN)* (2011). 55, 57, 225

Chapter 4

Accelerometer-Based Gait Analysis, A survey

Abstract

From a technological perspective, biometric gait recognition can be categorized into three approaches: Machine Vision based, Floor Sensor based and Wearable Sensor based. This survey covers historical development and current state of the art in accelerometer-based gait analysis, a sub-category of wearable sensor based gait recognition. It gives an all-around literature study describing the major modules; experiments, data acquisition, data analysis and comparison of gait representations.

4.1 Introduction

A particular way or manner of moving on foot is the definition for gait. Every person has his or her own way of walking. Several human factors, such as aging, injuries, operations on the foot etc. may change a person's walking style into a slight different walk, either permanent or temporary. Elders have a reduced range of hip motion at faster walking speeds and 5 degrees less hip extension than in their in younger age [14]. It also appears from early medical studies that there are twenty-four different components to human gait, and that if all the measurements are considered, gait is unique [4]. This has made gait recognition an interesting topic to be used for identifying individuals by the manner in which they walk. Furthermore, Figure 4.1 illustrates the complex biological process of the musculo-skeletal system, which can be divided into numerous types of sub events of human-gait. The instances that are shown in that figure are used to extract parameters for being used as an identification system of each individual.

The analysis of biometric gait recognition has been studied for a longer period of time

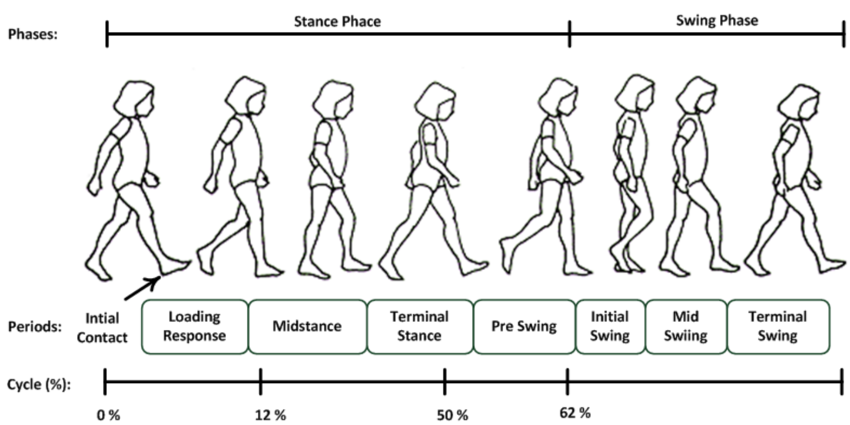


Figure 4.1: Division of the gait cycle into five stance phase periods and two swing phase periods [22].

[19, 20, 21, 29, 15] for the use in identification, surveillance and forensic systems and is becoming important, since they provide more reliable and efficient means of identity verification.

There are three different approaches in gait recognition; *Machine Vision Based (MV)*, *Floor Sensor based (FS)* and *Wearable Sensor based (WS)*. In the machine vision approach, the system will typical consist of several digital or analog cameras (black-and-white or color) with suitable optics for acquiring the gait data. Using techniques such as thresholding which converts images into simply black and white; pixel counting to count the number of light or dark pixels; or background segmentation, which performs a simple background subtraction could be some of the possible ways to identify a person.

In the floor sensor approach the sensors are placed along the floor (on a mat) where gait data is measured when people walk across. What differs the FS-based from the MV-based is the force to the ground by humans walk, this is also known as the GRF (Ground Reaction Force).

In contrast to video-based and floor-sensor based gait recognition, this survey is intended to provide a thorough review of the use of the accelerometer based gait recognition which is in the category of wearable-based gait recognition.

This paper is structured as follows: Section 4.2 gives a table overview research description of the accelerometer based gait analysis. The section surveys related papers and goes in deep details with the experiments, data acquisition, data analysis and comparison of results. Section 4.3 gives an description of how wearable gait recognition can be improved by proposing new methods for future work. Finally, section 4.4 shortly gives a summary of the paper.

4.2 Accelerometer Based Gait Analysis

Apart from the machine vision (MV) based and floor sensor (FS) based gait recognition, the wearable sensor based gait approach is the newest. This is based on attaching or wearing motion recording sensors on the body of the person in different places; on the waist, pockets, shoes and so forth.

The wearable sensors (WS) can have several purposes due to retrieving numerous types of data. Sensors of different types can for instance be accelerometers (measures acceleration), gyro sensors (measure rotation), force sensor (measures the force when walking) etc, but most literature so far has put a great focus on accelerometer based gait recognition.

A WS-based gait recognition application can improve authentication in electronic devices. An example would be to implement the application in mobile phones. Due to the unobtrusive way of collecting data it can be applied for continuous-verification of the identity in mobile phones. This means that for each step a user performs, the users identity will be re-verified to ensure that it is not another person who has the mobile phone in hand, but the same user is authenticated.

Some of the newer mobile phones now-a-days, e.g. the iPhone, use built-in accelerometers to detect when the device is rotated, so it can tell whether to display what's on the screen in vertical or horizontal format. This allows the user to decide which format is best for viewing, such as a photo, web page, video. Moreover, the device can further detect when it is being lifted to the ear so that phone calls are answered automatically.

Researching at different methodologies to analyzing the features of gait is increasing and become a popular area of research, especially in gait biometrics. Feature extraction from gait signals is a crucial for the efficient gait recognition. For a general gait analysis the signal processing flow is shown in Figure 4.2.

4.2.1 Experiments

To the best of our knowledge, no public database has been created for accelerometer based gait recognition. However, researchers have made own experiments and databases. Table

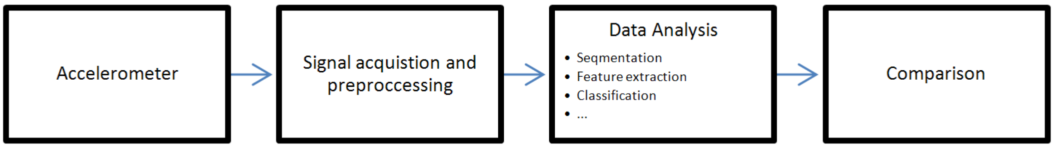


Figure 4.2: Signal processing flow of method for gait verification/identification.

4.1 summarizes experiments performed in research with the type of activity performed, environment and the range of walking per subject.

Table 4.1: Experiments Summary.

Study	Walking activities	Environment	Range (meter)
[8]	different speed	indoor hospital	10
[17]	normal	indoor	20
[7]	normal	indoor	100
[27]	normal, fast, slow	long corridor (stone plates)	50
[24][23]	normal	indoor	30
[3]	treadmill (normal, fast, slow)	-	-
[11]	free normal,fast,slow	overall	-
[9]	normal, fast, slow, circle	hall (solid surface)	20 m

All of the mentioned experiments above except [11] are *controlled experiment*. A controlled experiment is a fixed laboratory setting and furthermore differs from a real world scenario. People usually place their cell phone into their pockets or holding it while the phone is continuously moving in different directions. The mobile phone rotates and is in much more use. In the fixed setting the phone is usually attached one place to the body at all times.

As can be seen further on the table, then the *amount of volunteers* are very dissimilar. Many of the experiments until today have had low number of test-subjects, which have resulted in different performance. Obviously this means that the recognition performance (viewed later in this paper) are not comparable since the number of volunteers are dissimilar.

One issue which is not mentioned in the studies are the *clothing*. Since gait is known to differ from one person to another, clothing might be a critical parameter affecting the gait-recognition results.

Finally, very few studies have researched gait-recognition with different behavioral settings. A study [9] have shown that the gait-signal of one person slightly changes from one day to another.

4.2.2 Data acquisition

Accelerometer data can be derived from several types of equipments; from a dedicated accelerometer, GPS device, mobile phone etc. An accelerometer measures acceleration in three axes/directions, first is x-direction (up-down), second is y-direction (forward-backward) and third is z-direction (sideways).

Table 4.2 gives an overview of the placement of sensors and sensor models that have been used in literature.

Accelerometers (whether they are built into cell phones or are dedicated devices) usually outputs *different sample-rates* per time unit. Most accelerometers have a low sample-rate/frequency while few have a high frequency rate. Moreover, some devices today contain multiple sensors, such as a gyroscope, magnetic-field etc.

Table 4.2: Data Acquisition Summary.

Study	Acquistion From	Device
[26]	shoe	MEMS accelerometer
[13]	breast/hip	cell phone accelerometer
[18]	whole body weight	force plate
[7]	ankle/pocket/arm/hip	3D accelerometer (MRS)
[24][23]	waist	3D accelerometer (analog)
[2]	leg	wireless accelerometer (Tmote Sky)
[11]	pockets	phone handset
[16]	waist	3D accelerometer (ADXL05, analog)
[1][17]	waist	3D accelerometer (ADXL202JQ, analog)
[27]	hip	cell phone accelerometer
[3]	ankle	MEMS accelerometer
[8]	elastic belt on body	3D accelerometer
[6][9]	hip	3D accelerometer (MRS)

4.2.3 Preprocessing

Preprocessing has been performed differently in literature. Measured acceleration signals are sometimes low-frequency components. The signals that are being outputted are easily affected by experiment environmental noise, such as electronic noise in the equipment, high frequency noise etc., which will obscure/reduce the clarity of the acceleration data. Table 4.3 overviews preprocessing methods applied.

Table 4.3: Examples of Preprocessing Approaches

Study	Type	Approach
[7]	Time interpolation	Linear time interpolation
[9]	Noise filter	Weighted moving average
[24]	Noise filter	Daubeshies wavelet (wavelet transform)

4.2.4 Data Analysis

Identifying users from gait patterns using accelerometers is based on the assumption that the gait acceleration profile (template) is unique to some extent for every person. First, a feature template vector that represents characteristics of the gait of the person to authenticate is computed and stored as the template. The same feature vector is computed during the authentication process and compared to the feature template.

The accelerometer data can be analyzed in two domains: time domain or frequency domain. In the time-domain, the three acceleration signals (x,y,z) change over time (t), whereas in the frequency-domain each frequency band over a range of frequencies is given. A given function or a given signal can be converted between the time and frequency domains with a pair of mathematical operators called a transformation. Therefore, researchers have to decide which of these two domains, one will work with. Or somehow combine them with each other.

4.2.5 Segmentation (Data Analysis)

Gait segmentation is the process of identifying "boundaries" in the gait signal(s). Gait segmentation is an important sub-problem and can be performed in various ways. Gait signals obtained from an individual are composed of periodic segments called gait cycles.

These cycles physically correspond to two consecutive steps of the individual. A gait cycle begins when one foot touches the ground and ends when that same foot touches the ground again as shown in Figure 4.3.

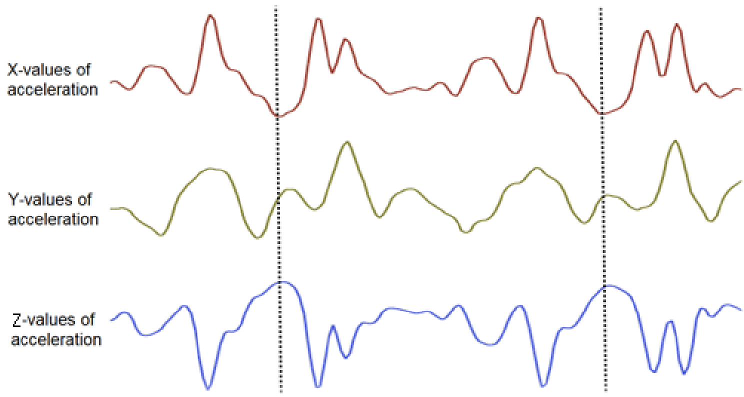


Figure 4.3: One gait cycle: begins when one foot touches the ground and ends when that same foot touches the ground again.

The end of one gait cycle is the beginning of the next. To split the signal into gait cycles, a determination of the gait cycle period is needed. This can be determined by either using the x, y and z data separately or a combination of two or three of the axes data.

Table 4.4 summarizes three segmentation approaches that has been applied so far.

Table 4.4: Experiments Summary.

Study	Segmentation Approach
[1][17]	Cycle Detection Algorithm (1 step extraction)
[7][9]	Cycle Detection Algorithm (2 steps extraction)
[2]	Period of an periodic gait cycle

4.2.6 Feature extraction in the time domain (Data Analysis)

The time domain is a term used to describe the analysis of signals, with respect to time as mentioned earlier. The *average cycle method* was one of the first methods applied in gait biometrics within the time domain and also the most applied. The average cycle method is a simple approach that averages all cycles extracted. However, other extraction approaches have also been developed. Table 4.5 shows these extractions that has been developed until recently.

Table 4.5: Time Domain Feature Approaches

Study	Approach
[1]	Average cycle detection
[6]	Matrix with cycles
[17]	N-bin normalized histogram
[27]	Cumulants of different orders

4.2.7 Feature extraction in the frequency domain (Data Analysis)

Extracting features in the frequency domain is a bit different than in the time domain, since other (mathematical) approaches has to be applied. One of the best known is the fourier transform. A fourier fransform is a mathematical operation that transforms a signal from the time domain to the frequency domain, and vice versa. Table 4.6 shows an overview of other applied methods.

Table 4.6: Frequency Domain Feature Approaches

Study	Approach
[24]	Discrete fourier Transform (DFT)
[3]	Fast fourier Transform (FFT)
[12]	Discrete cosine Transform (DCT)
[18]	Discrete wavelet transform (DWT)
[13]	Wavelet packet decomposition (WPD)

4.2.8 Comparison functions (Data Analysis)

Usually when two feature vectors are compared to each other the use of a comparison function is applied. One example could be a distance metric function. In mathematics, the metric or distance function is a function which defines a distance between elements of a set. There are infinite numbers of distance functions developed. All depending on the metric, distance function give very different results. This has a major impact in the authentication and therefore it is important to find or create a suitable metric. In biometrics it is interesting in knowing the similarity of one person to another. Table 4.7 shows the comparison functions used.

Table 4.7: Comparison Approaches

Study	Comparison Metric
[1]	Cross-correlation
[7]	Absolute (manhattan) distance
[9]	Euclidean distance
[6]	Dynamic time warping (DTW)

4.2.9 Classification (Data Analysis)

Another well-studied area that is used within gait recognition is the (un)supervised learning approaches. Within wearable gait recognition, a supervised learning is a machine learning approach for deducing a function from gait signal training data. The training data consist of pairs of input objects, that are extracted from the accelerometer signals. The output of the function can be a continuous value, called regression, or can predict a class label of the input (feature vector), called classification. An overview is shown in Table 4.8.

From an authentication point of view in data analysis and as mentioned earlier, the purpose is to create a template that represents the subject. Accelerometer based gait recognition has been explored since 2005, resulting in data analysis methods like the Average Cycle Method (ACM). The ACM became popular because of its simplicity as a feature extraction method for template creation. As seen throughout this literature study, many different features were used for creation of templates and comparison, such as correlation, cumulants, histogram similarity, ACM, FFT coefficients, and other regular features. It is difficult to estimate whether some of these techniques are general practical for any given

Table 4.8: Classification Approaches

Study	Comparison Metric
[27]	Support Vector Machine (SVM)
[27]	Principal Component Analysis (PCA)
[2]	Linear Discriminant Analysis (LDA)
[26]	multilayer perception neural network
[13]	Kohonen self-organizing map (KSOM)

data from different devices, since the experiments performed and analyses applied varied to a larger tend.

4.2.10 Comparing gait representations

Unlike video-based gait biometric, no public data-set on wearable gait is available. This makes the comparison issue more difficult when comparing multiple private-sets with eachother. Thus, no direct comparison can be considered in this section. On the other hand, all results will still be overviewed.

In Table 4.9 is a short summary of current WS-based gait recognition studies from years 2004 to 2010 is shown. The last column, #TP, represents the number of test-persons.

Study	EER	Recognition	#TP
[5]	1.68	-	60
[7]	5 %	-	30
[25]	5.6 %	-	21
[6]	5.7 %	-	60
[9]	5.9 %	-	60
[1]	6.4 %	-	36
[17]	7.0 % , 19.0 %	-	36
[28]	13.7 %	-	31
[10]	-	96.93 %	9
[10]	-	96.93 %	9

Table 4.9: Performance of current wearable sensor-based gait recognitions. Excerpt of best EER from each author.

4.3 Discussion and Future Directions

This section discusses problem issues in accelerometer based gait analysis and proposes future work.

4.3.1 Experiment Proposal:

Fixed laboratory settings have shown great performance over time. To make gait recognition more reliable, then some issues needs to be taken into consideration. E.g. the wearing of the accelerometer device (e.g. a cell phone). By not placing the phone in a fixed position as has been done until now would make the experiment more realistic.

Time is an important factor in an experiment. The more time one experiment last, the more data will be retrieved. To this, a subject must wear the attached accelerometer device over longer time. In addition, the subject should be experimented in different types of activities (activity recognition). Recently [11] analyzed activity recognition, unfortunately with few volunteers. Thus, it is strongly proposed that different activities are performed during the experiments.

As seen in Table 4.9 the numbers of subjects participating in experiments are very dissimilar. Experiments with low number of subjects statistically gives imprecise estimations when calculating recognition rates.

Clothes wearing might have an influence on the gait-appearance. This has to be further researched. Another issue related to clothes wearing is shoe wearing. As has been seen in work of [7], shoes slightly changes gait from one person to another. Therefore, several types of walking settings most be applied including abnormal behaviors.

Gait slightly changes over time and human factors (e.g. tiredness, laziness, illness, etc.). Experiments shall note these types of issues. Most papers during this survey does not mention these factors.

4.3.2 Data Analysis Proposal:

Data acquisition is one of the major parts that has a great influence in the data analysis. For example, accelerometer values which are outputted from a cell phone differ from one phone to another. Phones usually have different embedded accelerometer chips, which outputs different values regarding to their sample-rate. Most of the phones today have low-cost accelerometers built-in, but still there are big differences in their qualities. A suggestion would be to investigate which accelerometers have the best low-cost quality sensor and to investigate how big a change sensors have in difference.

Lately, a paper was written by [5] applying the use of principal component analysis (PCA) to wearable sensor based gait recognition and as an additional step in the Average Cycle Method. The PCA is mostly used in the exploratory data analysis and was known to give good recognition rates, it has been used in machine vision based gait recognition before. An EER of 1.68% was achieved during the work. This is an great improvement by around a factor of 3.5 compared to the best known results on the same private database. A strong suggestion for further improvements in performance is to look closer at different distance metrics since most simple metrics have been investigated. The merit of these results is not only the improvement of the gait recognition performance, but this can also be seen as a first step to a combination of recognizing not only that a person is walking (as opposed to for example sitting, running, cycling, etc.), but also who the person is (either identifying or authenticating that person).

Since accelerometer data conducts signals as output based on time, it is most obvious that one take a deep look into digital signal processing (DSP). DSP is concerned with the representation of signals by a sequence of numbers and the processing of these signals. The main idea of DSP is usually to measure, filter and/or compress continuous real-world signals like gained here as gait signals. DSP algorithms have long been run on standard computers, on specialized processors called digital signal processors (DSPs), or on purpose-built hardware such as application-specific integrated circuit (ASICs). Today there are additional technologies used for digital signal processing including more powerful general purpose microprocessors, field-programmable gate arrays (FPGAs), digital signal controllers (mostly for industrial applications such as motor control), and stream processors, among others. In DSP, researchers usually study digital signals in the time domain (one-dimensional signals), spatial domain (multidimensional signals), frequency domain, autocorrelation domain, and wavelet domains. The domain in which to process a signal is done by making an informed guess (or by trying different possibilities) as to which domain best represents the essential characteristics of the signal. Therefore it is strongly proposed that DSP approaches are considered and analyzed for the data processing. Few examples such as the FFT, DWT, cross-correlation have been tried out already, but the information retrieved has not been so specific. Furthermore, the average cycle method is not a fully automated gait recognition method and therefore DSP could be used for the same purpose making the process automatic and more reliable.

Multi-modal biometric is today considered a major-topic in biometric systems and might also be useful within accelerometer based gait recognition. Mobile devices today have several types of built-in sensor (e.g. gyroscopes, magnetic field sensors etc.) which eventually outputs some data that might be combined with each other. Fusion of the three directions (x,y,z) might also be fused, which might further have a great impact improving authentication performances.

The creation of a public database for accelerometer based gait recognition is highly recommendable to have. A suggestion would be to collect data and to conduct databases consisting of several settings (normal/slow/fast walking, going up/down stairs) so researchers have the ability to compare their algorithms and results with each other.

Finally, as seen through out this paper, activity recognition research has been studied slightly using accelerometers, thus, additional research has to be studied. Since more and more mobile devices are embedding additional sensors than only accelerometers (such as gyro-scopes, magnetic field sensors, rotation sensors, etc.), an interesting point in gait recognition research is to apply multiple sensors.

4.4 Conclusion

Unlike most of the previous work in gait recognition, using machine vision or floor sensor based approaches, a current state of the art of the accelerometer based gait biometrics has been studied. It gives an overview of papers describing their experiments, acquisition, data-analysis and results.

The main advantage here is to provide unobtrusive user authentication and identification. There are many factors that can influence the accuracy of this system. These factors has to be taken into consideration towards developing a robust system. Therefore, accelerometer based gait biometrics is still in its infancy and still additional research needs to be worked out and considered. Since wearable based gait biometrics started back in 2005 then there has been an increasingly interest within this topic until today. Furthermore, no public database has been created within this research field which makes the comparison of two research works more difficult to distinguish from one another. Also algorithms developed for performance evaluation would be more convenient when a public database is available.

4.5 Bibliography

[1] AILISTO, H. J., LINDHOLM, M., MANTYJARVI, J., VILDJIOUNAITE, E., AND MAKELA, S.-M. Identifying people from gait pattern with accelerometers. *In Proceedings of the SPIE 5779* (2005), 7–14. 64, 65, 66, 67, 97, 108

[2] ANNADHORAI, A., GUENTERBERG, E., BARNES, J., HARAGA, K., AND JAFARI, R. Human identification by gait analysis. In *HealthNet '08: Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments* (New York, NY, USA, 2008), ACM, pp. 1–3. 64, 65, 67

[3] BÄCHLIN, M., SCHUMM, J., ROGGEN, D., AND TÖSTER, G. Quantifying gait similarity: User authentication and real-world challenge. In *ICB '09: Proceedings of the Third International Conference on Advances in Biometrics* (Berlin, Heidelberg, 2009), Springer-Verlag, pp. 1040–1049. 63, 64, 66

[4] BENABDELKADER, C., CUTLER, R., NANDA, H., AND DAVIS, L. S. Eigengait: Motion-based recognition of people using image self-similarity. In *AVBPA* (2001), pp. 284–294. 61

[5] BOURS, P., AND SHRESTHA, R. Eigensteps: A giant leap for gait recognition. In *2nd International Workshop on Security and Communication Networks (IWSCN 2010)* (Karlstad, Sweden, 5 2010). 67, 68

[6] DERAWI, M. O., BOURS, P., AND HOLIEN, K. Improved cycle detection for accelerometer based gait authentication. In *International Conference on Intelligent Information Hiding and Multimedia Signal Processing - Special Session on Advances in Biometrics* (2010). 64, 65, 66, 67

[7] GAFUROV, D. *Performance and Security Analysis of Gait-based User Authentication*. Ph.D. thesis, Faculty of Mathematics and Natural Sciences, University of Oslo, 2008. 63, 64, 65, 66, 67, 68

[8] HENRIKSEN, M., LUND, H., MOE-NILSSEN, R., BLIDDAL, H., AND DANNESKIOD-SAMSE, B. Test-retest reliability of trunk accelerometric gait analysis. *Gait Posture 19*, 3 (2004), 288–97. Available from: `http://www.biomedsearch.com/nih/Test-retest-reliability-trunk-accelerometric/15125918.html`. 63, 64

[9] HOLIEN, K. Gait Recognition under non-standard circumstances, Master thesis, Gjøvik Univeristy College, 2008. 63, 64, 65, 66, 67

[10] HUANG, B., CHEN, M., HUANG, P., AND XU, Y. Gait modeling for human identification. In *International Conference on Robotics and Automation* (2007), pp. 4833–4838. 67, 97

[11] HYNES, M., WANG, H., AND KILMARTIN, L. Off-the-shelf mobile handset environments for deploying accelerometer based gait and activity analysis algorithms. *Conf Proc IEEE Eng Med Biol Soc 1* (2009), 5187–90. Available from: `http://www.biomedsearch.com/nih/Off-shelf-mobile-handset-environments/19964383.html`. 63, 64, 68

[12] IBRAHIM, R., AMBIKAIRAJAH, E., CELLER, B., LOVELL, N., AND KILMARTIN, L. Gait patterns classification using spectral features. In *IET Irish Signals and Systems Conference (ISSC)* (2008). 66

[13] ISO, T., AND YAMAZAKI, K. Gait analyzer based on a cell phone with a single three-axis accelerometer. In *MobileHCI '06: Proceedings of the 8th conference on Human-computer interaction with mobile devices and services* (New York, NY, USA, 2006), ACM, pp. 141–144. 64, 66, 67

[14] KERRIGAN. Kerrigan's unique research may unlock elder gait enigma. http://oscar.virginia.edu/researchnews/x11269.xml. [Online; accessed 27-September-2010]. 61

[15] LARSEN, P., SIMONSEN, E., AND LYNNERUP, N. Gait analysis in forensic medicine. *J Forensic Sci* (2008). 61, 73, 75

[16] LEE, C.-Y., AND LEE, J.-J. Estimation of walking behavior using accelerometers in gait rehabilitation. *International Journal of Human-friendly Welfare Robotic Systems 3*, 32–36. 64

[17] MANTYJARVI, J., LINDHOLM, M., VILDJIOUNAITE, E., MAKELA, S.-M., AND AILISTO, H. Identifying users of portable devices from gait pattern with accelerometers. *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP '05) 2* (2005), ii/973 – ii/976. 63, 64, 65, 67, 96, 97, 108

[18] MOSTAYED, A., KIM, S., MAZUMDER, M. M. G., AND PARK, S. J. Foot step based person identification using histogram similarity and wavelet decomposition. In *ISA '08: Proceedings of the 2008 International Conference on Information Security and Assurance (isa 2008)* (Washington, DC, USA, 2008), IEEE Computer Society, pp. 307–311. 64, 66

[19] NIXON, M. S., CARTER, J. N., SHUTLER, J., AND GRANT, M. New advances in automatic gait recognition. *Elsevier Information Security Technical Report 7*, 4 (2002), 23–35. Available from: `http://eprints.ecs.soton.ac.uk/7904/`. 61

[20] NIXON, M. S., TAN, T. N., AND CHELLAPPA, R. *Human Identification based on Gait*. International Series on Biometrics. Springer, 2005. Available from: `http://eprints.ecs.soton.ac.uk/11573/`. 61, 106

[21] NIYOGI, S., AND ADELSON, E. Analyzing and recognizing walking gures in xyt. *in Conference of Computer Vision and Pattern Recognition* (1994). 61, 96, 106

[22] PERRY, J. History of the study of locomotion. http://www.univie.ac.at/cga/history/modern.html. [Online; accessed 27-September-2010]. ix, 61

[23] RONG, L., JIANZHONG, Z., MING, L., AND XIANG, H. Identification of individual walking patterns using gait acceleration. *In 1st International Conference in Bioinformatics and Biomedical Engineering* (2005), 543–546. 63, 64

[24] RONG, L., JIANZHONG, Z., MING, L., AND XIANGFENG, H. A wearable acceleration sensor system for gait recognition. In *Industrial Electronics and Applications, 2007. ICIEA 2007* (2007), pp. 2654–2659. 63, 64, 66

[25] RONG, L., ZHIGUO, D., JIANZHONG, Z., AND MING, L. A wearable acceleration sensor system for gait recognition. *In 2nd IEEE Conference on Industrial Electronics and Applications* (2007), 2654–2659. 67, 97, 108

[26] SAZONOV, E., BUMPUS, T., ZEIGLER, S., AND MAROCCO, S. Classification of plantar pressure and heel acceleration patterns using neural networks. In *International Joint Conference on Neural Networks, IJCNN '* (2005), IEEE. 64, 67

[27] SPRAGER, S., AND ZAZULA, D. Gait identification using cumulants of accelerometer data. In *SENSIG'09/VIS'09/MATERIALS'09: Proceedings of the 2nd WSEAS International Conference on Sensors, and Signals and Visualization, Imaging and Simulation and Materials Science* (Stevens Point, Wisconsin, USA, 2009), WSEAS, pp. 94–99. 63, 64, 65, 67

[28] VILDJIOUNAITE, E., MÄKELÄ, S.-M., LINDHOLM, M., RIIHIMÄKI, R., KYLLÖNEN, V., MÄNTYJÄRVI, J., AND AILISTO, H. Unobtrusive multimodal biometrics for ensuring privacy and information security with personal devices. In *Pervasive* (2006), pp. 187–201. 67, 97, 108, 113

[29] WANG, L., TAN, T., HU, W., AND NING, H. Automatic gait recognition based on statistical shape analysis. *IEEE Transactions on Image Processing 12*, 9 (2003), 1120–1131. 61

Chapter 5

Towards Continuous Authentication Based on Gait Using Wearable Motion Recording Sensors

Abstract

Nearly all systems conduct some kind of user authentication before granting access to the objects or services. Moreover, humans pass through authentication steps more than once in their everyday activity, e.g. for entering a house you have to possess the correct key to open the door, to use a computer you need to know its password, etc. These authentications are one-time or static which means once the user's identity is verified the authentication lasts forever. However, some high security systems require ensuring the correct identity of the user throughout the full session. This then requires verification of user identity continuously or periodically. One of the important requirements for continuous authentication is that the method should be unobtrusive and convenient in usage. If this is not satisfied the users are not going to accept continuous authentication. Therefore not all authentication methods can be suitable for continuous authentication even if they provide higher security.

In this chapter we present continuous authentication using gait biometric. Gait is a person's manner of walking and gait recognition refers to the identification and verification of an individual based on gait. This chapter discusses advantages and disadvantages of gait biometrics in the context of continuous authentication. Furthermore, we present a framework for continuous authentication using gait biometrics. The proposed framework extends on traditional static (one-time) user authentication. The framework can also be applied to other biometric modalities with small modifications.

5.1 Introduction

A particular way or manner of moving on foot is a definition for gait [15]. Every person has his or her own way of walking. From early medical studies it appears that there are twenty-four different components to human gait, and that if all the measurements are considered, gait is unique [9]. This has made gait recognition an interesting topic to be used for identifying individuals by the manner in which they walk. Figure 5.1 illustrates the complex biological process of the musculo-skeletal system, which can be divided into several types of sub events of human-gait. The instances that are shown in this figure are used to extract parameters for being used as an identification system of each individual.

The analysis of biometric gait recognition has been studied for a longer period of time [32, 41, 42, 43, 53] for the use in identification, surveillance and forensic systems and is becoming important, since it can provide more reliable and efficient means of identity verification.

Today, computer systems demand authentication in case of using the system. Typically, the authentication is performed at login time either with a password, token, biometric characteristic and/or a combination of these. Performing the last mentioned might give further guarantee that the claimed user logging in is the authorized user instead of a bur-

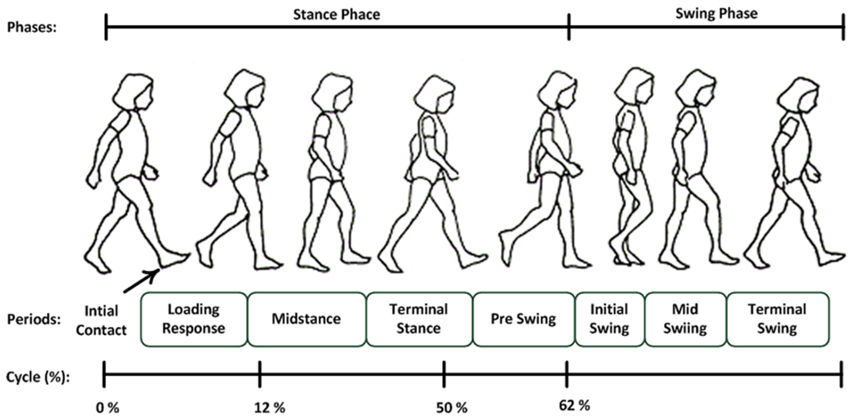


Figure 5.1: Division of the gait cycle into five stance phase periods and two swing phase periods.

glar. However, once the user has been granted access; most systems assume that the user is continuously legitimated into the system.

In critical or high security environments, it should be ensured that the user must be the legitimated throughout usage. Therefore, user authentication needs to be performed in a continuous way within the time the system is actively being used. Furthermore, authentication needs to be "*attractive*" for the user. This means that in the authentication process the users do not need to do anything special, like for example periodically entering a password. Continuous authentication using biometrics can fit these needs Thus, one of the important requirements in continuous authentication is unobtrusiveness, since this can be monitored in a non-intrusive way. The Wearable Sensor (WS) based method can be a very good candidate to fulfill this requirement, compared to current knowledge-based mechanisms.

This chapter is structured as follows: Section 'Background' gives the state of the art overview of gait recognition and activity recognition. Section 'Evaluation of a Biometric System' introduces the definition of static and continuous authentication. The next section introduces the biometric continuous authentication (CA) system using gait recognition. This is the major contribution in this paper and discusses CA using gait. The last section concludes the paper and gives a description on how wearable gait recognition can be improved by proposing new ideas for future work.

5.2 Background / State of the art

This section is divided into 2 subsections. First subsection describes the motion-based (gait biometrics) identity verification. Second subsection introduces activity recognition.

5.2.1 Gait Recognition

From how the walking data is collected, gait recognition can be categorized in three approaches [20]:

- Video Sensor Based (VS);
- Floor Sensor based (FS);
- Wearable Sensor based (WS).

We will give a short description on all three approaches, but we will mainly focus on the WS-based approach. We will illustrate how nicely this WS-based approach meets the requirements of continuous authentication which were specified in the previous section.

5.2.1.1 Video Sensor Based

In the VS-based approach, the system will typically consist of several video cameras with suitable optics for acquiring the gait data. Using techniques such as thresholding which converts images into simply black and white; pixel counting to count the number of light or dark pixels; and background segmentation, which performs a simple background subtraction could be some of the possible ways to identify a person. Figure 5.2 shows an example of the VS-based approach with processed background segmentation.

Figure 5.2: Background segmentation for extracting the silhouette picture - subtraction

Scientist have during the last decade until currently been working on analyzing the movements of criminals caught on CCTV and compare them with those of a suspect [51]. Back in December 2004, there was a case where a perpetrator robbed a bank in Denmark [32]. During the robbery, two surveillance cameras were recording the crime scene. One camera was placed at the entrance recording the robber in frontal view (walking in, standing and walking inside the bank during the robbery, and leaving the bank). The other camera was placed inside the bank recording the cashier's desk. The court used the gait-analysis tool to find the perpetrator of the robbery. Almost at the same time in late December 2004, there was a murder crime scene in the United Kingdom. A podiatrist told the supreme court jury that there were matches between the person captured on video and known videos of the murderer [11]. In a third case, around mid-April 2008, a burglar was caught because of his bow-legged walk [8]. Even though that the burglars face was hidden, it was still possible to identify the burglar. In most cases in a robbery, usually the perpetrator wears a mask and gloves to hide his body characteristics such as face and hands so that no face or fingerprints can be shown or found at the crime scene. If cameras are available that recorded the gait of the burglar, then maybe enough information is present to link a person to the crime.

5.2.1.2 Floor Sensor Based

In the FS-based approach the sensors are placed on or in the floor where gait data is measured when people walk across. In the FS-based approach the force to the ground by human walking is measured. This is also known as the GRF (Ground Reaction Force). In a research from the University of Southampton, such a floor sensor for gait recognition was prototyped as illustrated in Figure 5.3.

5.2.1.3 Wearable-Sensor Based

Apart from the MV-based and FSbased gait recognition, the WS-based gait approach is the most recent. This approach is based on attaching or wearing motion recording sensors on the body of the person in different places; on the waist, pockets, shoes and so forth, see Figure 5.4

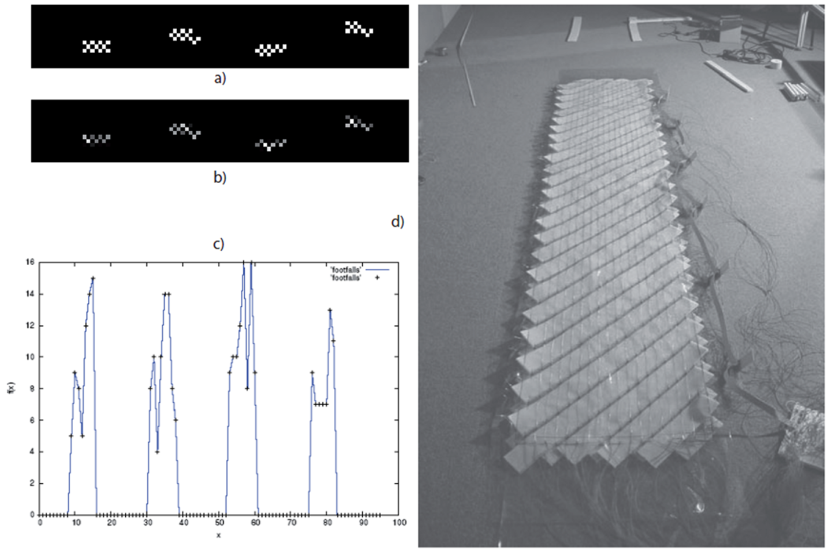


Figure 5.3: Gait collection by floor sensors. a) shows footsteps recognized, b) shows the time spent at each location in a), c) shows footstep profiles for heel and toe strikes (x and f(x) indicate the heal/toe locations and footfalls forces, respectively) , and finally d) is a picture of a prototype floor sensor carpet.

Figure 5.4: Sensor attached at various locations.

The WS-based approach can serve several purposes due to retrieving numerous types of data. Different types of sensors can for example be accelerometers (measuring acceleration), gyro sensors (measuring rotation), force sensor (measuring force of walking) etc. Most literature so far used accelerometer based gait recognition. Thus, these accelerometers are becoming an important tool into our every-day. Most of the modern mobile smart phones nowadays use built-in accelerometers to detect when the device is rotated. The data from the accelerometers is used to display the information on the screen in either horizontal or vertical format. Moreover, the device can further detect when it is being lifted to the ear so that phone calls can be answered automatically. Feature extraction from gait signals is important for the efficiency of gait recognition. For a general gait analysis the signal processing flow is shown in Figure 5.5

A WS-based gait recognition application can improve authentication in electronic devices. One of the advantages of WS-based gait recognition and the main argument towards CA is its unobtrusiveness. An example would be to integrate the Motion Recording Sensor (MRS) in clothing (e.g. footwear) or personal electronics of the user.

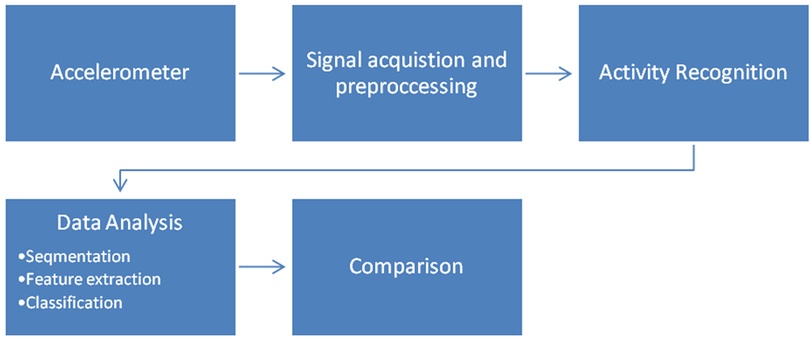


Figure 5.5: Processing flow of method for gait verification.

Whenever a user walks, the MRS can record motion and the recorded motion can be used for identity verification purposes unobtrusively in the background. Due to the unobtrusive way of collecting data it can be applied for continuous verification of the identity in mobile phones. This means that for each step a user takes, the identity of the user will be re-verified to ensure that the user has not changed. In addition, MRS are cheap and many recent personal electronic devices (e.g. mobile phone) are already equipped with such sensors.

Experiments To the best of our knowledge, no public database has been created for accelerometer based gait recognition. However, researchers have made their own experiments and databases. Table 5.1 summarizes experiments performed in research with the type of activity performed, environment and the number of subjects.

Study	Walking activities	Subjects
[6]	treadmil(normal, fast, slow)	5
[26]	free normal, free resting	5
[48]	normal, fast, slow	6
[22]	normal	20
[45, 46]	normal	21, 35
[21]	normal	21, 30, 50, 100
[37]	normal	36
[24]	normal, fast, slow, circle	60

Table 5.1: Experiments Summary

All of the mentioned experiments above except [26] are controlled experiments. A controlled experiment is defined as taking place under fixed laboratory settings and differs significantly from a real world scenario. People usually carry their mobile phones in their pockets or hold them while the phone is continuously moving and rotating in different directions. In the fixed, controlled settings the phone is usually attached to one particular location on the body at all times.

As can be seen further in Table 5.1 , the amount of volunteers differs greatly. Many of the experiments had a low number of volunteers. Obviously this means that the recognition performances (viewed later in this paper) are not directly comparable since the numbers of volunteers are dissimilar.

Finally, very few studies have researched gait-recognition with different behavioral settings. A study [24] has shown that the gait-signal of one person slightly changes from one day to another.

Data acquisition Accelerometer data can be derived from several types of sensors; from a dedicated accelerometer, a GPS device, a mobile phone etc. An accelerometer measures acceleration in three directions, being the x-direction (up-down), the y-direction (forward-backward) and the z-direction (sideways).

Table 5.2 gives an overview of the placement of sensors and sensor models that have been used in literature.

Study	Acquisition Form	Subjects
[47]	shoe	MEMS accelerometer
[28]	breast/hip	cell phone accelerometer
[40]	whole body weight	force plate
[21]	ankle/pocket/arm/hip	3D accelerometer (MRS)
[45, 46]	waist	3D accelerometer (analog)
[5]	leg	wireless accelerometer(Tmote Sky)
[26]	pockets	phone headset
[33]	waist	3D accelerometer (ADXL05, analog)
[2, 37]	waist	3D accelerometer (ADXL202JQ, analog)
[48]	hip	cell phone accelerometer
[6]	ankle	3D accelerometer
[22]	elastic belt on body	3D accelerometer
[14, 24]	hip	3D accelerometer (MRS)

Table 5.2: Data Acquisition Summary

Accelerometers (whether they are built into cell phones or are dedicated devices) usually output different sample-rates per time unit. Most accelerometers have a low sample-rate/frequency while few have a high frequency rate. Moreover, some devices today contain multiple sensors, such as a gyroscope, magnetic-field etc.

Preprocessing Preprocessing has been performed differently in literature. [24] and [21] applied the *linear time interpolation* on the three axis data (x,y,z) retrieved from the sensor to obtain an observation every X seconds since time intervals between two observation points were not always equal.

Measured acceleration signals are sometimes low-frequency components. The signals that are being outputted are easily affected by experiment environmental noise, such as electronic noise in the equipment, high frequency noise etc. which will obscure/reduce the clarity of the acceleration data. However, the accelerometer does not always measure gravitational acceleration; it might also measure the acceleration of light oscillation brought by the body of the human. This results in another weakness from the sensor that is acceleration data will be outputted with some noise. [24] and [21] removed this type of noise by using a *weighted moving average* filter which is fast and easy to implement, whereas [40] and [46] de-noised the signals with a Daubechies wavelet (wavelet transform). They meant that this transform showed satisfying results in noise suppression from previous experiments, preserving edges and would be helpful for the gait segmentation.

Since different accelerometers output different unit values, [24] and [21] had to convert their values into practical unit values (e.g. g-forces) by using properties of the sensor they derived the data from.

In the last preprocessing step, [24] and [21] calculated the resultant vector (also known as the vector magnitude) by applying the following formula,

$$r_t = \sqrt{x_t^2 + y_t^2 + z_t^2},\ t = 1..., N$$

where r_t, x_t, y_t and z_t are the magnitudes of resulting, vertical, horizontal and lateral acceleration at time t, respectively and N is the number of recorded observations in the signal.

However, for example [48] did not use any combined vector, but instead kept the vector as is so they had a 3-component vectors of samples stored in a matrix A

$$A = [\mathrm{x}\,\mathrm{y}\,z]$$

where x, y and z represents vectors of acquired samples for each spatial direction.

Data Analysis Identifying users from gait patterns using accelerometers is based on the assumption that the gait acceleration profile ("reference template") is unique to some extent for each and every person. First, a feature vector that represents the characteristics of the gait of the person to authenticate is computed and stored as the reference template. A similar feature vector is computed during the authentication process and compared to the reference template. Acceptance of the user is based on the distance between the new feature vector and the reference template.

The accelerometer data can be analyzed in two domains: the time domain or the frequency domain. In the time domain, the three acceleration signals (x,y,z) change over time (t), whereas in the frequency domain each frequency band over a range of frequencies is used. A given function or a given signal can be converted between the time and the frequency domain with a pair of mathematical operators called a transformation.

Segmentation (Data Analysis) Gait segmentation is the process of identifying "boundaries" in the gait signal(s). Gait segmentation is an important sub-problem and can be performed in various ways. Gait signals obtained from an individual are composed of periodic segments called gait cycles. These cycles physically correspond to two consecutive steps of the individual. A gait cycle begins when one foot touches the ground and ends when that same foot touches the ground again as shown in Figure 1 and the acceleration data is illustrated in Figure 5.6.

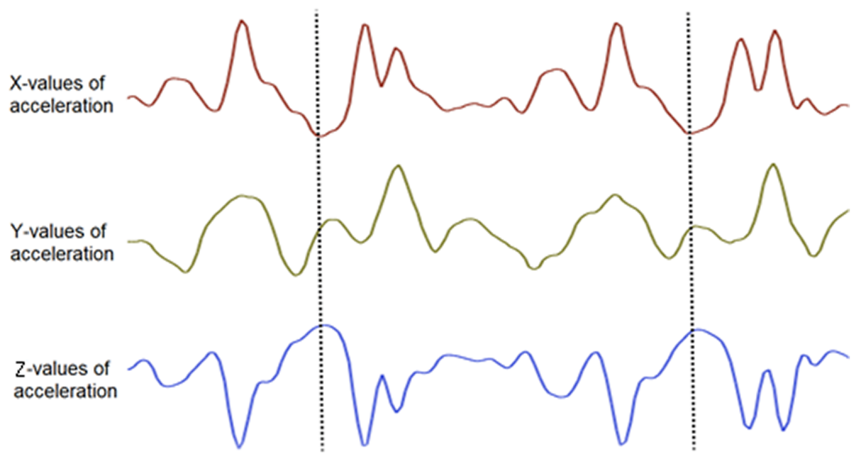


Figure 5.6: One gait cycle: begins when one foot touches the ground and ends when that same foot touches the ground again.

The end of one gait cycle is the beginning of the next. To split the signal into gait cycles, a determination of the gait cycle period is needed. This can be determined by either using the x, y and z data separately or a combination of the data of two or three directions.

Table 5.3 summarizes three segmentation approaches that have been applied so far.

Study	Approach
[5]	Period of an periodic gait cycle
[2, 37]	Cycle Detection Algorithm (1 step extraction)
[21, 24]	Cycle Detection Algorithm (2 step extraction)

Table 5.3: Segmentation Approaches

Feature extraction in the time domain (Data Analysis) The time domain is a term used to describe that the analysis of signals is done with respect to time, as mentioned earlier. The average cycle method was one of the first methods applied in gait biometrics within the time domain and also the most applied. The average cycle method is a simple approach that averages all cycles extracted. However, other extraction approaches have also been developed. Table 5.4 shows these extractions that have been developed until recently.

Study	Approach
[14]	Matrix with cycles
[2]	Average cycle detection
[37]	N-bin normalized histogram
[48]	Cumulants of different orders

Table 5.4: Time Domain Feature Approaches

Feature extraction in the frequency domain (Data Analysis) Extracting features in the frequency domain is a bit different than in the time domain, since other (mathematical) approaches have to be applied. The best known approach is the Fourier transform, which is a mathematical operation that transforms a signal from the time domain to the frequency domain, and vice versa. Table 5.5 shows an overview of other applied methods.

Study	Approach
[46]	Discrete Fourier Transform (DFT)
[6]	Fast Fourier Transform (FFT)
[27]	Discrete Cosine Transform (DCT)
[40]	Discrete Wavelet Transform (DWT)
[28]	Wavelet Packet Decomposition (WPD)

Table 5.5: Frequency Domain Feature Approaches

Comparison functions (Data Analysis) Usually when two feature vectors are compared to each other the use of a comparison metric is applied, for example a distance function. In mathematics, a metric or distance function is a function which defines the distance between elements of a set. Many different distance functions have been developed. The obtained results in the various researches depend on the particular distance functions that are used. Given a particular dataset, then the performance results differ for different distance functions. This has a major impact on authentication and therefore it is important to find or create an adequate distance function. Table 5.6 shows which comparison metrics are used.

Classification (Data Analysis) Another well-studied area that is used within gait recognition is the (un)-supervised learning approaches. Supervised learning is a machine learning

Study	Comparison Metric
[2]	Cross-correlation
[21]	Absoulte (Manhattan) Distance
[24]	Euclidean Distance
[14]	Dynamic time warping (DTW)

Table 5.6: Comparison Approaches

approach of extracting a function from supervised training data, in which each sample has a pair of input objects and a desired output value. Within wearable gait recognition, the training data consist of pairs of input objects that are extracted from the accelerometer signals. The output of the function can be a continuous value, called regression, or can predict a class label of the input (feature vector), called classification. An overview is shown in Table 5.7

Study	Comparison Metric
[48]	Support Vector Machine (SVM)
[48]	Principal Component Analysis (PCA)
[5]	Linear Discriminant Analusis (LDA)
[48]	Multilayer perceptrons-neural network
[28]	Kohonen self-organizing map (KSOM)

Table 5.7: Classification Approaches

From an authentication point of view in data analysis and as mentioned earlier, the purpose is to create a reference template that represents the subject. Accelerometer based gait recognition has been explored since 2005, resulting in data analysis methods like the Average Cycle Method (ACM). The ACM became popular because of its simplicity as a feature extraction method for template creation. Many different features were used for creation of templates and comparison, such as correlation, cumulants, histogram similarity, ACM, FFT coefficients, and other regular features. It is difficult to estimate whether some of these techniques are in general practical for any given data from different devices, since the experiments performed and analyses applied varied to a larger extent.

Comparing gait performances Unlike VS-based gait biometric, no public data-set on WS-based gait is available. This makes performance comparison more difficult because each result is based on a private data set. Therefore, no direct comparison can be considered in this section, but we will still give an overview of all reported performance results.

Table 5.8 shows a short summary of current WS-based gait recognition studies from 2004 to 2010. The last column, #TP, represents the number of test-persons.

5.2.2 Activity Recognition

Wearable sensors have been shown to be adequate for activity recognition. This recognition is a required step towards continuous authentication in WS-based gait authentication using sensors in mobile devices. These devices come prepared with sensors such as accelerometers, gyro-scopes, Global Positioning Systems (GPS), etc., which can gather information about the actions of a user. For example, a phone might observe that a user is walking normally in a non-stressed environment, or it might make decisions regarding whether incoming phone calls should be answered or denied

Figure 5.7 illustrates an excerpt of which activities can be recognized from the gait signal data.

Study	EER	Recognition	TP
[25]	-	96.93 %	9
[39]	-	97.4 %	10
[46]	5.6 %	-	21
[21]	5 %	-	30
[52]	13.7 %	-	31
[2]	6.4 %	-	36
[37]	7.0 % , 19.0 %	-	36
[10]	1.68%	-	60
[14]	5.7%	-	60
[24]	5.9%	-	60

Table 5.8: Performances of current wearable sensor-based gait recognitions

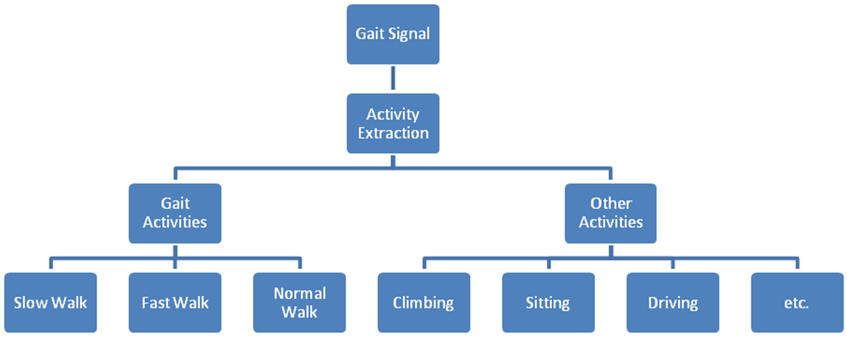


Figure 5.7: Different activities.

Several applications for recognizing activities from sensor data have been implemented in a broad range of fields such as health care [29] , fitness [12, 35], and security [1]. Different types of sensors have been applied, e.g., accelerometer data for recognizing physical activities [3, 35, 38] and both mobile phone usage data [16] and GPS data [31, 36] for human mobility analysis

Detecting primitive everyday activities, such as walking, running, biking, sitting and laying have in laboratory settings been analyzed by several researchers [4, 18, 17, 19, 50]. In all these studies data is collected using accelerometers built into wearable sensing devices. Most research has shown recognition accuracy above 85% on large, complex data sets using standard linear signal processing methods and a lot of signal statistics computations executed. Furthermore, "high weighted" feature extractions approaches were used to decide whether these features would be useful for classification. Whilst these methodologies work fine, they need a lot of computing power. This will benefit applications suited for real-time detection of activities on low-powered devices, such as mobile phones. The applicability of the results which were presented in the studies mentioned above to out-of-lab monitoring is vague. In the study of [18] the recognition performance decreased from 95.8% to 66.7% as the experiment was shifted from inside to outside the laboratory. Furthermore, recognition of dissimilar activities involving dynamic motion has not yet been studied in detail. In some studies data has been composed outside the laboratory. The subjects placed accelerometers on their sternum, wrist, thigh, and lower leg. The same activities, i.e. sitting, standing, laying, and talking were recognized with an overall accuracy of 66.7%. In [7] five biaxial accelerometers attached to hip, wrist, arm, ankle, and thigh were used to recognize twenty everyday patterns. From 82 to 160 min of data was collected and a decision tree classifier was used for classification. The range of the recognition accuracies varied from 41% to 97% for different patterns

Other research groups have studied activity recognition as fraction of context awareness research [7, 30, 34]. Context sensing and use of context information is a significant part of the ubiquitous computing scenario [13, 49]. The purpose of context sensing is to provide a computing device (e.g., cellular phone, or a device integrated into clothes) with some "senses", with which it becomes attentive of its environment. With these "senses", the computing device is then able to observe and measure its surroundings and it will then become aware of its own context. The context describes the condition or status of the user or the device. Different devices can use the context information in special ways, e.g. for offering relevant services and information, for adapting its user interface, for annotating a digital diary (e.g. energy expenditure), etc. Location and time belong to the set of the most important contexts and the use of these contexts has been researched widely. However, to recognize the physical activities of a person, a sensor-based approach is required

A very interesting research paper [44] studied the automatic classification of physical activities. The paper described how automatic classification of everyday activities can be used for promotion of health-enhancing physical activities and a healthier life-living. The application could therefore be used for an "activity diary" program that would explain to the user which activities were performed during the day and what the daily cumulative durations of each activity were. When the user is given this information, the user can draw his own conclusions and further adjust his behavior accordingly. This model is known as the behavioral feedback model. This model is being effectively used in for example weight management programs. Alternatively the activity diary information can be utilized by context-aware services and devices that propose adapted information or adapt their user interface (UI) based on the user's activity type.

The latest and most successful algorithm has been implemented in real time on a mobile phone by [19] who proposed an alternative approach for representing time series data that significantly has lowered the memory and computational complexity. The memory and computational savings are crucial, given that for many applications, activity recognition would have to run in real time as a small component of a larger system on a low-powered mobile device. The study used accelerometer data; intuitively, the acceleration recorded by the mobile phone attaching this to the hips and legs. The techniques from nonlinear time series analysis [23] was adopted to extract features from the time series. These features were used as inputs to an off-theshelf classifier. The approach improves classification performance while at the same time it extracts fewer features from the time series data

5.3 Evaluation of a Biometic System

5.3.1 Static Authentication

As can be seen in Figure 5.8, the user initially presents its biometric modality (e.g. gait) to the sensor equipment (e.g. an accelerometer sensor in a mobile phone), which captures it as raw biometric data (e.g. a discrete time signal). After preprocessing this raw biometric data, features will be extracted from the data. In case of gait biometrics, these features would typically be periodic cycles. The extracted features can then be used for comparison against corresponding features stored in a database, based on the claimed identity of the user. The result of the comparison is called the similarity score, S where a low value of S indicates little similarity, while a high value indicates high similarity. The last step is to compare the similarity score S to a predefined system threshold T, and output a decision based on both values. In case the similarity score is above the threshold (S>T) then the user is accepted as genuine, while a similarity score below the threshold (S<T) indicates an impostor who is rejected by the system.

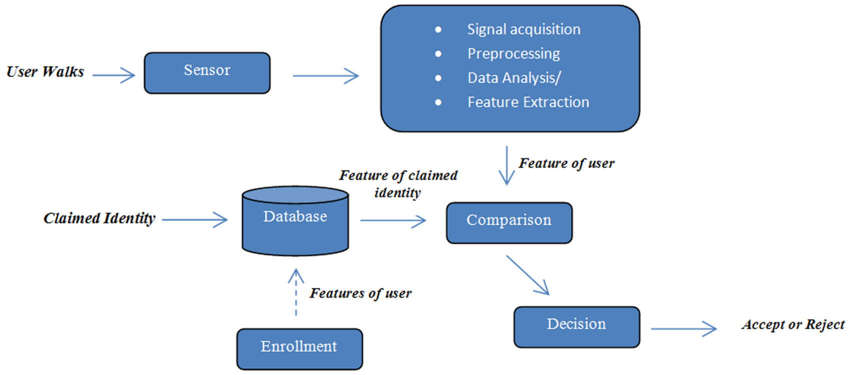


Figure 5.8: A traditional verification process (one-time static).

Obviously the biometric features of the user must initially be stored in the database before any comparison of a new biometric input can take place. This is done during the enrollment phase of a biometric system. During the enrollment phase also raw biometric data is captured from the biometric modality, after which it is processed and features are extracted. The extracted data is now stored in a database and linked to the identity of the user who enrolled. The stored data in the database is referred to as the (reference) template of the user. In case of gait biometrics it is very well possible that the raw biometric data is captured multiple times and these multiple samples are combined to make a single template. This is a well known technique in behavioral biometrics.

The calculation of the False Match Rate (FMR) and False Non-Match Rate (FNMR) is done in the following way. Suppose we have collected N data samples from each of M participants, then we can calculate similarity scores between two samples, either being from one person or from two different persons. A similarity score between two samples from the same person is called a genuine score, while an impostor score is the similarity score between two samples from different persons. Given our setting, we can have N*M data samples from which we can calculate the total number of $N_{Gen} = M*N*(N-1)/2$ different genuine scores and $N_{Imp} = M*N*(M-1)*N/2$. Given these sets of genuine and impostor scores we can calculate FMR and FNMR for any given threshold T as follows:

$$FMR(T) = \frac{\text{number of imposter scores } \leq \text{ T}}{\text{N}_{\text{Imp}}}$$

$$FNMR(T) = \frac{\text{number of genuine scores } > \text{ T}}{\text{N}_{\text{Gen}}}$$

Given various values of the threshold we can create a Decision Error Tradeoff (DET) curve which shows the relation between FMR and FMNR for various threshold values T. From this, we can find the point where FNMR equals FMR, or in other words the Equal Error Rate (EER). This rate is very common used value which is being used to compare different systems against each other, and it roughly gives an idea of how well a system performs.

5.3.2 Continuous Authentication

In a continuous authentication system we can no longer evaluate the performance of the system in terms of FMR and FNMR. In a static authentication system, the question is if a claimed identity is genuine or not. In a continuous authentication system the question is if the identity of the current user is still the same as the identity of the user that logged on the system. In particular, in continuous authentication the most important issue is not *if* an impostor is rejected by the system, but *how fast* he will be rejected. In a static biometric system, the lowest EER indicates the best performance. Similarly in a continuous authentication system, the best performance is indicated by the fastest rejection of impostors. A desirable property of a continuous authentication system might furthermore be that genuine users will never be rejected by the system, although this might not be realistic. In case a genuine user gets rejected, then this should obviously take much longer time in comparison to rejection of impostors.

In a continuous authentication system we also have to create a reference template for each user, which will be used for comparison against newly inputted raw biometric data. However, the resulting similarity score S will not directly lead to the rejection or acceptance of a user. First of all, as the user is already using the system, he/she is accepted by default, so in case of continuous authentication, we only have to consider the rejection of a user. Consider the situation where the genuine user is providing new biometric data to the system that is rather dissimilar to the stored reference template. This is a common situation in behavioral biometrics as biometric data is never exactly the same when it is presented to the sensor. This low similarity should not immediately result in a rejection of the user by the system, but merely in a lowered trust of the genuineness of this user. Similarly, if the similarity score S is high, indicating a high similarity between the reference template and the new biometric data, then the trust in the genuineness of the current user increases. This implies that the level of trust that the system has in the genuineness of the user fluctuates. In case of a genuine user, the level of trust will in general stay high, while for an impostor the level ideally should drop as fast as possible. There will be a system threshold such that a trust level below the threshold will result in a lock out of the current user and a fall back to a static authentication procedure (which can but need not be a biometric system). In terms of performance of a continuous authentication system, we can then say that the faster impostors are detected (and locked out) the better the system performs.

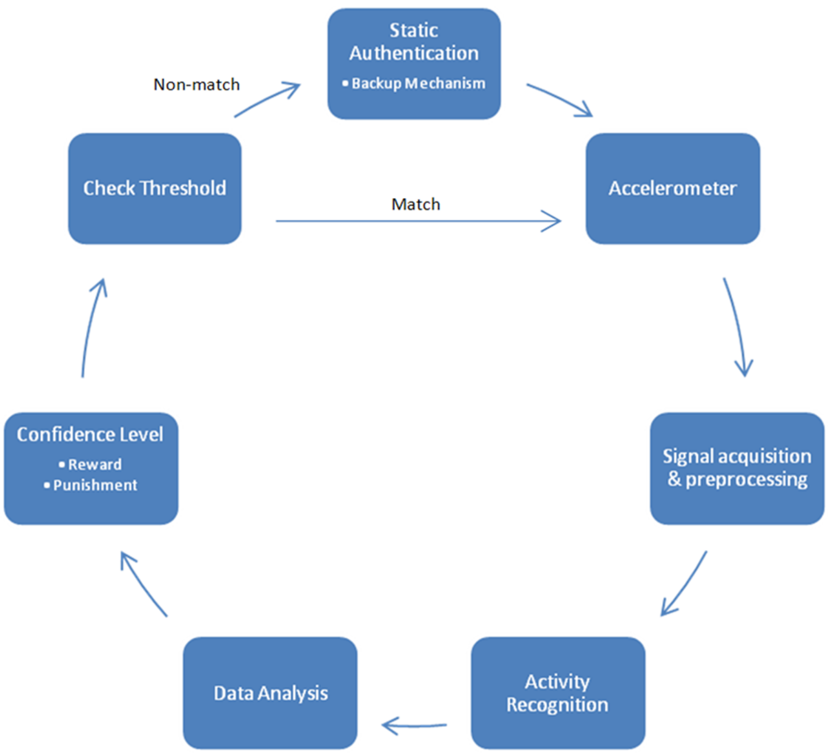


Figure 5.9: Continuous Authentication using Gait.

Figure 5.9 represents the foundation of a CA system using gait on how to verify an identity of the user continuously. The main distinction between static and continuous gait verification is that for continuous gait verification the *data analysis*, *evaluation* and *authorization* are no longer one-time static happening. They are now elements of a continuous procedure.

5.4 Evaluation of a Continous Authentication System

In this section we will describe in more detail how a continuous authentication system can be evaluated. In particular we will describe the changes in confidence level by introducing so-called "penalty-and-reward" functions. We will assume that the biometric data is collected from accelerometers in a mobile phone that is worn by a user while walking.

Activity Identification Contributions within wearable gait recognition until now have only focused on the task of person identification where data was retrieved from dedicated external sensors.

One important issue in continuous authentication and gait recognition is to develop and evaluate algorithms to detect physical activities from data acquired using mobile devices (built-in sensors) worn on different parts of the body, which is also known as either *activity identification* or *activity recognition*.

Because wearable gait recognition research has had its focus on feature extraction and performance evaluation, the activity identification has not been analyzed to a large extent in wearable gait authentication before and especially not in gait recognition using mobile devices As described in the section on Activity Recognition, we see that researchers have not had the intention of analyzing activity recognition with respect to gait recognition. Activity identification is required in order to be able to perform continuous gait authentication under normal everyday walking circumstances, using mobile devices. Therefore activity identification will be the first step towards protecting mobile devices against unauthorized use of the device and disclosure of information present on the device. Without an activity identifier on the mobile device, it is quite difficult to know exactly what activity a subject is performing at a certain time. The gait recognition should only be functioning when the subject is physically active, and thus, the recognition should not be activated when the subject is passive (sitting down, standing, etc.).

Data Analysis The data analysis part in continuous gait recognition is similar to the data analysis in static gait recognition. After walking activity has been identified, the walking signal has to be segmented and the segmented walking signal needs to be analyzed further. There are multiple ways of analyzing the data in wearable based gait recognition. Some approaches are described in the State of the Art section. The research on wearable sensor based gait recognition so far has only focused on "high grade" collection devices (high sample rate, large sample scale). The research on wearable sensor gait recognition using the accelerometer data from mobile phones or other mobile user devices does rarely exist. Sensor hardware (accelerometer, gyroscopes, etc.) on different mobile devices will be of different quality and therefore a broad selection of mobile phones and mobile user devices needs to be analyzed carefully As the sensors in the mobile devices are of lesser quality (lower sample rate and/or lower sample scale) the performance of a gait recognition system will be not as good as compared to the high grade collection devices. Therefore research should focus on optimizing the performance for mobile devices.

Confidence Level Function A confidence level is a new term in biometrics. It can be used as a realistic and easy to implement step/module in continuous authentication in general and continuous gait recognition in particular. This module is designed and located after the feature extraction and before the decision making as illustrated in Figure 5.9. The confidence level is updated continuously based on user actions and will go up or down, based upon the similarity between the current user action and the reference template. The limitation of static biometric analysis is that the authentication process is performed at the end of a full walking session and not during the session itself. In such a case we can only afterwards decide if the user was genuine or not, which is obviously too late. Therefore it is very important to introduce the idea of the confidence level function for continuous authentication

Basically, a confidence level function is a function which updates a confidence value (C) for every captured feature during the walking session. The initial confidence value is set right after the static authentication and its value is 100.

Based on the distance between the current feature and the reference template, a decision rule is used to either increase or decrease the confidence value C. In particular, the confidence value will decrease each time the distance between the current feature and the reference template is outside the expected range, i.e. is above some pre-defined threshold. The value will increase each time this distance is below that pre-defined threshold. In other words the user should be punished when he/she makes mistakes (decreasing the confidence value) and he/she should be rewarded (increasing the confidence value) when he/she walks correctly. A setup for the confidence level function will look like follows:

$$C = \begin{cases} 100 & \text{initial value} \\ C - punishment & \text{mistake} \\ C + reward & \text{correct} \end{cases}$$

We should note that the confidence value C is initially set to 100 (100% confidence in the genuineness of the current user) and that it cannot rise above that. This means that in case of a reward the value of C increases, but is still bounded by 100. Similarly the confidence level value C cannot be lower than zero. The actual values C=100 and C=0 indicate complete trust in the current user and complete distrust.

As mentioned before, there is a decision function that, based on the distance D between the current feature and the reference template, and based on a global threshold T decides whether the current action of the user was correct or wrong, i.e. if the user should be rewarded or punished. Generally speaking, if $D \leq T$ then the user is rewarded and if $D > T$ he is punished. There are various ways to define a punishment or a reward. For example for the punishment, one solution could be to decrease the value C with a fixed constant. Another option could be to decrease C by the difference between the distance D and threshold T Similar approaches can be taken for the reward. In fact there are no restrictions against combining a fixed reward value with a variable punishment.

In cases where data from an impostor are compared against a genuine user's reference template, the confidence level value is expected to generally keep decreasing. The impostor should be denied access after a relatively low number of user actions i.e. after a short walking time. This means that he cannot easily compensate his wrong walking by accidentally also walking correctly, i.e. walking as described in the reference template of the genuine user. However, when comparing data of a genuine user with its own template, the confidence level value should more or less fluctuate near the initialization value, meaning that wrong walking is easily compensated by correct walking.

Decision Rule: As described earlier in the section of static gait recognition a decision rule is based on a predefined threshold. The score value which is gained from the comparison-metric is compared to the threshold. Multiple decision rules could be implemented and applied This mechanism can be easily translated to continuous gait authentication, by comparing the trust level to a pre-defined system threshold. If the value of the trust level C drops below a system threshold T_{trust}, then the system will lock out the user. Instead of using a system wide threshold could the system also be implemented with user defined thresholds. A user who is very stable in his way of walking could then have a higher personal threshold then a user who is less stable, i.e. is more likely to be punished for incorrect walking.

Backup Authentication Mechanism When a user is locked out by the CA mechanism, a backup authentication mechanism should be activated. The user is rejected when the value of the confidence level C, as described in an earlier section, is under a certain system wide or personal threshold. This means that the system decides to deny the user further access and, thus, we enter a new state as illustrated in Figure 5.9 The state which will be entered is the static authentication state. This state must enable us to reset the confidence level in order to use the phone and the CA mechanism again. For example, if a user of a mobile phone gets rejected, the phone goes into the locked state. The user will now be able to enter the PIN code to open the phone from its locked state. Once the correct PIN code is entered, the user will return to the normal state and start with the highest trust level again.

Continuous Authentication – Multi Level Security As described in the previous section we can use the trust level and a threshold to determine if a user needs to be locked out or not. This mechanism can actually be extended in such a way that Multi Level Security (MLS) can be provided. As mentioned before the value of the trust level C lies within the interval between 0 and 100. In the simple case a single threshold T is used such that the user gets locked out when $C<T$ and stays logged in as long as $C \geq T$. In principle a user can perform all actions as long as he is logged in.

The system can be extended such that we have multiple thresholds $T < T_1 < \ldots < T_{n-1}$. For simplicities sake assume n=3 here, so we have three different thresholds and $T < T_1 < T_2$. In this setting a user will be locked out of the system if the value of the trust level $C<T$ and he can perform all actions if $C \geq T_2$. In case $T \leq C < T_1$ then the user still will be logged on to the system, but he will not be able to perform all actions, for example he will only be able to make phone calls but he has no more access to any information stored on the phone. In case $T_1 \leq C < T_2$ then the user will be granted some more privileges besides making phone calls, but he will not have full access, for example he might then have access to data on the phone, but not be granted access to Wi-Fi.

As the value of C varies continuously the user will lose or regain access to particular privileges. Whenever a user wants to perform a particular action the CA system will check the value C of the trust level with the thresholds stored in the phone and decide if particular actions are allowed or not. Figure 5.10 illustrates an example of how the resources are related to the trust level.

5.5 Conclusion and Future Work

Ensuring the correct identity of a user throughout a full session is important, especially for high security applications. In static biometric user authentication the authentication mechanism will make a decision about the correctness of the claimed user identity directly after the user has inputted his biometric feature. This decision is either accepting or rejecting this user, resulting in either access or not to the particular system. System performance is measured in terms of mistakes that are made by making the decision, i.e. in terms of FMR and FNMR.

The first difference for a continuous biometric user authentication mechanism is that the user is by default accepted due to the fact that his or her identity has been verified by a static authentication mechanism. A biometric CA mechanism will therefore only reject users if they have proven not to be the genuine user. In order to be able to measure the genuineness of the user we introduced trust levels and a way to adjust the trust level based on newly defined penalty and reward functions. The performance of a continuous authentication system is measured in terms of how long it takes before an impostor is detected and locked out by the system.

In this chapter we focused on continuous user authentication using biometric gait recognition. In our approach gait is collected using wearable motion recording sensors attached to the person's body. One of the advantages of using WS-based gait recognition in contin-

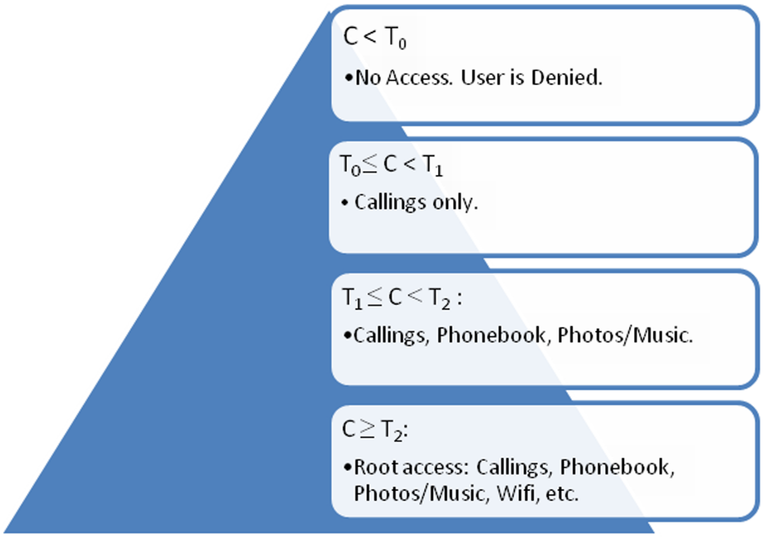


Figure 5.10: Pyramid Authentication: Continuous authorization and Confidence Level.

uous authentication is its unobtrusiveness. Whenever a user walks his identity is verified implicitly in the background without distracting the user from his normal activity. The proposed framework extends the traditional static authentication to account for periodic/continuous (re-)verification of identity. The proposed continuous authentication framework can easily be adjusted for other biometric modalities which are suitable for CA.

Future work will be to implement the proposed continuous gait authentication mechanism as an application in mobile phones and measure exact performances, i.e. the time it takes before impostor users are recognized as such by the CA mechanism and are locked out of the system.

5.6 Bibliography

[1] *A Framework For Activity-Specific Human Identification* (2002). 82

[2] AILISTO, H. J., LINDHOLM, M., MANTYJARVI, J., VILDJIOUNAITE, E., AND MAKELA, S.-M. Identifying people from gait pattern with accelerometers. *In Proceedings of the SPIE 5779* (2005), 7–14. 22, 29, 32, 33, 78, 80, 81, 82, 132, 133, 134

[3] AMINIAN, K., AND NAJAFI, B. Capturing human motion using body-fixed sensors: outdoor measurement and clinical applications: Research articles. *Comput. Animat. Virtual Worlds 15* (May 2004), 79–94. Available from: http://portal.acm.org/citation.cfm?id=1071202.1071206. 82, 132, 135

[4] AMINIAN, K., ROBERT, P., BUCHSER, E., RUTSCHMANN, B., HAYOZ, D., AND DEPAIRON, M. Physical activity monitoring based on accelerometry: validation and comparison with video observation. *Medical and Biological Engineering and Computing 37* (1999), 304–308. 10.1007/BF02513304. Available from: http://dx.doi.org/10.1007/BF02513304. 82, 132

[5] ANNADHORAI, A., GUENTERBERG, E., BARNES, J., HARAGA, K., AND JAFARI, R. Human identification by gait analysis. In *HealthNet '08: Proceedings of the 2nd Inter-*

national Workshop on Systems and Networking Support for Health Care and Assisted Living Environments (New York, NY, USA, 2008), ACM, pp. 1–3. 22, 33, 35, 78, 80, 81, 131, 133, 134, 135, 137, 148

[6] BÄCHLIN, M., SCHUMM, J., ROGGEN, D., AND TÖSTER, G. Quantifying gait similarity: User authentication and real-world challenge. In *ICB '09: Proceedings of the Third International Conference on Advances in Biometrics* (Berlin, Heidelberg, 2009), Springer-Verlag, pp. 1040–1049. 22, 30, 77, 78, 80, 132, 133, 134, 135

[7] BAO, L., AND INTILLE, S. S. Activity Recognition from User-Annotated Acceleration Data. *Pervasive Computing* (2004), 1–17. Available from: `http://www.springerlink.com/content/9aqflyk4f47khyjd`. 36, 37, 39, 40, 82, 83

[8] BBC-NEWS. How can you identify a criminal by the way they walk? http://news.bbc.co.uk/2/hi/uk_news/magazine/7348164.stm. [Online; accessed 21-Feb-2012]. 75

[9] BENABDELKADER, C., CUTLER, R., NANDA, H., AND DAVIS, L. S. Eigengait: Motion-based recognition of people using image self-similarity. In *AVBPA* (2001), pp. 284–294. 73

[10] BOURS, P., AND SHRESTHA, R. Eigensteps: A giant leap for gait recognition. In *2nd International Workshop on Security and Communication Networks (IWSCN 2010)* (Karlstad, Sweden, 5 2010). 31, 33, 82, 132

[11] CANADANEWS. Forensic gait analysis points to accuse. http://www.canada.com/victoriatimescolonist/news/story.html?id=19d99f1a-bb4d-4d89-a92e-e7a583b1d14f. [Online; accessed 21-Feb-2012]. 75

[12] CHOUDHURY, T., CONSOLVO, S., HARRISON, B., HIGHTOWER, J., LAMARCA, A., LEGRAND, L., RAHIMI, A., REA, A., BORDELLO, G., HEMINGWAY, B., KLASNJA, P., KOSCHER, K., LANDAY, J., LESTER, J., WYATT, D., AND HAEHNEL, D. The mobile sensing platform: An embedded activity recognition system. *Pervasive Computing, IEEE 7*, 2 (2008), 32 –41. 82

[13] COUTAZ, J., CROWLEY, J. L., DOBSON, S., AND GARLAN, D. Context is key. *Commun. ACM 48* (March 2005), 49–53. Available from: `http://doi.acm.org/10.1145/1047671.1047703`. 83

[14] DERAWI, M. O., BOURS, P., AND HOLIEN, K. Improved cycle detection for accelerometer based gait authentication. In *International Conference on Intelligent Information Hiding and Multimedia Signal Processing - Special Session on Advances in Biometrics* (2010). 32, 33, 78, 80, 81, 82, 132

[15] FARLEX. The free dictionary. http://www.thefreedictionary.com/gait. [Online; accessed 21-Feb-2011]. 73

[16] FARRAHI, K., AND GATICA-PEREZ, D. What Did You Do Today? discovering Daily Routines from Large-Scale Mobile Data. Tech. rep., 2008. To appear in ACMMM08. 82, 132

[17] FOERSTER, F., AND FAHRENBERG, J. *Motion pattern and posture: correctly assessed by calibrated accelerometers*, vol. 32 of *3*. 2000. Available from: `http://www.biomedsearch.com/nih/Motion-pattern-posture-correctly-assessed/11029819.html`. 82

[18] FOERSTER, F., SMEJA, M., AND FAHRENBERG, J. Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring. *Computers in Human Behavior 15*, 5 (1999), 571 – 583. Available from: http://www.sciencedirect.com/science/article/B6VDC-3WS6PFV-3/2/395540fe937d0effdc490e2ead48658f. 82, 132

[19] FRANK.J, M., AND PRECUP.D. *Activity and Gait Recognition with Time-Delay Embeddings*. 2010. Available from: http://aaai.org/ocs/index.php/AAAI/AAAI10/paper/view/1666. 20, 22, 82, 83

[20] GAFUROV, D. *Performance and Security Analysis of Gait-based User Authentication*. Ph.D. thesis, Faculty of Mathematics and Natural Sciences, University of Oslo, 2008. 74, 155

[21] GAFUROV, D. *Performance and Security Analysis of Gait-based User Authentication*. Ph.D. thesis, Faculty of Mathematics and Natural Sciences, University of Oslo, 2008. ix, 17, 20, 22, 25, 27, 29, 30, 31, 32, 33, 77, 78, 80, 81, 82

[22] HENRIKSEN, M., LUND, H., MOE-NILSSEN, R., BLIDDAL, H., AND DANNESKIOD-SAMSRE, B. Test-retest reliability of trunk accelerometric gait analysis. *Gait Posture 19*, 3 (2004), 288–97. Available from: http://www.biomedsearch.com/nih/Test-retest-reliability-trunk-accelerometric/15125918.html. 20, 22, 77, 78

[23] HOLDGER KANTZ, T. S. Nonlinear time series analysis. *The Economic Record 84* (2008), 396–397. Available from: http://econpapers.repec.org/RePEc:bla:ecorec:v:84:y:2008:i:266:p:396-397. 83, 132

[24] HOLIEN, K. Gait Recognition under non-standard circumstances, Master thesis, Gjøvik University College, 2008. ix, 20, 21, 22, 23, 24, 25, 26, 27, 32, 33, 77, 78, 80, 81, 82, 133, 135

[25] HUANG, B., CHEN, M., HUANG, P., AND XU, Y. Gait modeling for human identification. In *International Conference on Robotics and Automation* (2007), pp. 4833–4838. 33, 82

[26] HYNES, M., WANG, H., AND KILMARTIN, L. Off-the-shelf mobile handset environments for deploying accelerometer based gait and activity analysis algorithms. *Conf Proc IEEE Eng Med Biol Soc 1* (2009), 5187–90. Available from: http://www.biomedsearch.com/nih/Off-shelf-mobile-handset-environments/19964383.html. 22, 77, 78

[27] IBRAHIM, R., AMBIKAIRAJAH, E., CELLER, B., LOVELL, N., AND KILMARTIN, L. Gait patterns classification using spectral features. In *IET Irish Signals and Systems Conference (ISSC)* (2008). 31, 35, 80, 131, 148

[28] ISO, T., AND YAMAZAKI, K. Gait analyzer based on a cell phone with a single three-axis accelerometer. In *MobileHCI '06: Proceedings of the 8th conference on Human-computer interaction with mobile devices and services* (New York, NY, USA, 2006), ACM, pp. 141–144. 22, 31, 33, 78, 80, 81

[29] KANG, D.-O., LEE, H.-J., KO, E.-J., KANG, K., AND LEE, J. A wearable context aware system for ubiquitous healthcare. In *Engineering in Medicine and Biology Society, 2006. EMBS '06. 28th Annual International Conference of the IEEE* (302006-sept.3 2006), pp. 5192 –5195. 82, 132, 134

[30] KORPIPÄÄ, P., KOSKINEN, M., PELTOLA, J., MÄKELÄ, S.-M., AND SEPPÄNEN, T. Bayesian approach to sensor-based context awareness. *Personal Ubiquitous Comput. 7* (July 2003), 113–124. Available from: http://dx.doi.org/10.1007/s00779-003-0237-8. 83, 134

[31] Krumm, J., and Horvitz, E. *Predestination: Inferring Destinations from Partial Trajectories*, vol. 4206 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, 2006. Available from: `http://dx.doi.org/10.1007/11853565_15`. 82, 132

[32] Larsen, P., Simonsen, E., and Lynnerup, N. Gait analysis in forensic medicine. *J Forensic Sci* (2008). 61, 73, 75

[33] Lee, C.-Y., and Lee, J.-J. Estimation of walking behavior using accelerometers in gait rehabilitation. *International Journal of Human-friendly Welfare Robotic Systems 3*, 32–36. 22, 78, 132, 134

[34] Lee, S.-W., and Mase, K. Activity and location recognition using wearable sensors. *Pervasive Computing, IEEE 1*, 3 (2002), 24 – 32. 83, 134, 137

[35] Lester, J., Choudhury, T., and Borriello, G. A Practical Approach to Recognizing Physical Activities. In *Pervasive Computing*, K. Fishkin, B. Schiele, P. Nixon, and A. Quigley, Eds., vol. 3968 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, Berlin, Heidelberg, 2006, ch. 1, pp. 1–16. Available from: `http://dx.doi.org/10.1007/11748625_1`. 82, 133, 137

[36] Liao, L., Fox, D., and Kautz, H. Extracting places and activities from gps traces using hierarchical conditional random fields. *Int. J. Rob. Res. 26* (January 2007), 119–134. Available from: `http://portal.acm.org/citation.cfm?id=1229555.1229562`. 82, 133, 134, 135

[37] Mantyjarvi, J., Lindholm, M., Vildjiounaite, E., Makela, S.-M., and Ailisto, H. Identifying users of portable devices from gait pattern with accelerometers. *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP '05) 2* (2005), ii/973 – ii/976. 20, 22, 33, 77, 78, 80, 82

[38] Mathie, M. J., Coster, A. C., Lovell, N. H., and Celler, B. G. Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement. *Physiological measurement 25*, 2 (April 2004). Available from: `http://view.ncbi.nlm.nih.gov/pubmed/15132305`. 82, 132

[39] Morris, S. J. *A shoe-integrated sensor system for wireless gait analysis and real-time therapeutic feedback*. Ph.D. thesis, Division of Health Sciences and Technology, Harvard University-MIT, 2004. 33, 82

[40] Mostayed, A., Kim, S., Mazumder, M. M. G., and Park, S. J. Foot step based person identification using histogram similarity and wavelet decomposition. In *ISA '08: Proceedings of the 2008 International Conference on Information Security and Assurance (isa 2008)* (Washington, DC, USA, 2008), IEEE Computer Society, pp. 307–311. 22, 24, 31, 78, 80

[41] Nixon, M. S., Carter, J. N., Shutler, J., and Grant, M. New advances in automatic gait recognition. *Elsevier Information Security Technical Report 7*, 4 (2002), 23–35. Available from: `http://eprints.ecs.soton.ac.uk/7904/`. 73

[42] Nixon, M. S., Tan, T. N., and Chellappa, R. *Human Identification based on Gait*. International Series on Biometrics. Springer, 2005. Available from: `http://eprints.ecs.soton.ac.uk/11573/`. 73

[43] Niyogi, S., and Adelson, E. Analyzing and recognizing walking gures in xyt. *in Conference of Computer Vision and Pattern Recognition* (1994). 73

[44] Parkka, J., Ermes, M., Korpipaa, P., Mantyjarvi, J., Peltola, J., and Korhonen, I. Activity classification using realistic data from wearable sensors. *Information Technology in Biomedicine, IEEE Transactions on 10*, 1 (2006), 119 –128. 83

[45] RONG, L., JIANZHONG, Z., MING, L., AND XIANG, H. Identification of individual walking patterns using gait acceleration. *In 1st International Conference in Bioinformatics and Biomedical Engineering* (2005), 543–546. 22, 40, 77, 78, 132, 134, 135

[46] RONG, L., JIANZHONG, Z., MING, L., AND XIANGFENG, H. A wearable acceleration sensor system for gait recognition. In *Industrial Electronics and Applications, 2007. ICIEA 2007* (2007), pp. 2654–2659. 20, 22, 30, 33, 77, 78, 80, 82

[47] SAZONOV, E., BUMPUS, T., ZEIGLER, S., AND MAROCCO, S. Classification of plantar pressure and heel acceleration patterns using neural networks. In *International Joint Conference on Neural Networks, IJCNN '* (2005), IEEE. 22, 33, 78, 134, 135

[48] SPRAGER, S., AND ZAZULA, D. Gait identification using cumulants of accelerometer data. In *SENSIG'09/VIS'09/MATERIALS'09: Proceedings of the 2nd WSEAS International Conference on Sensors, and Signals and Visualization, Imaging and Simulation and Materials Science* (Stevens Point, Wisconsin, USA, 2009), World Scientific and Engineering Academy and Society (WSEAS), pp. 94–99. 22, 30, 33, 77, 78, 79, 80, 81

[49] STREITZ. NORBERT, N. P. The disappearing computer. *Commun. ACM* (2005), 32–35. Available from: `http://dx.doi.org/10.1145/1047671.1047700`. 35, 83, 131

[50] SUBRAMANYA, A., RAJ, A., BILMES, J., AND FOX, D. Recognizing activities and spatial context using wearable sensors. 494–502. 82, 134

[51] TIMESONLINE. Aiming to catch criminals red-footed. http://business.timesonline.co.uk/tol/business/law/article685365.ece. [Online; accessed 21-Feb-2012]. 75

[52] VILDJIOUNAITE, E., MÄKELÄ, S.-M., LINDHOLM, M., RIIHIMÄKI, R., KYLLÖNEN, V., MÄNTYJÄRVI, J., AND AILISTO, H. Unobtrusive multimodal biometrics for ensuring privacy and information security with personal devices. In *Pervasive* (2006), pp. 187–201. 33, 82

[53] WANG, L., TAN, T., HU, W., AND NING, H. Automatic gait recognition based on statistical shape analysis. *IEEE Transactions on Image Processing 12*, 9 (2003), 1120–1131. 73

Chapter 6

Unobtrusive User-Authentication on Mobile Phones using Biometric Gait Recognition

Abstract

The need for more security on mobile devices is increasing with new functionalities and features made available. To improve the device security we propose gait recognition as a protection mechanism. Unlike previous work on gait recognition, which was based on the use of video sources, floor sensors or dedicated high-grade accelerometers, this paper reports the performance when the data is collected with a commercially available mobile device containing low-grade accelerometers. To be more specific, the used mobile device is the Google G1 phone containing the AK8976A embedded accelerometer sensor [5]. The mobile device was placed at the hip on each volunteer to collect gait data. Preproccesing, cycle detection and recognition-analysis were applied to the acceleration signal. The performance of the system was evaluated having 51 volunteers and resulted in an equal error rate (EER) of 20%.

6.1 Introduction

Mobile devices – mobile phones, PDAs etc. – can be found in almost everyone's pocket and are considered as an essential tool in human-being's everyday life. They are not only used for mere communication such as calling or sending text messages; however, these devices are also used in applications such as internetting, receiving and sending emails and storing (sensitive) documents. As a result of this, not only phone numbers and addresses are stored in the mobile device but also financial information and business details which definitely should be kept private. Thus the value of the data on the phone is often higher than the pure costs of the phone itself and therefore this data should be protected. Most mobile phones do only offer authentication methods where the user has to remember a number (PIN) which he explicitly has to enter. This is not very user friendly, so many users decide to demand this authentication only once when the phone is switched on. A survey [6] shows that 66% of the respondents use PIN-authentication only at switch on and only 18% of the user also utilize the standby mode authentication. As a consequence, when a phone is lost or stolen, in most cases, all data on the phone is directly available to the new holder. This situation can be improved by offering an unobtrusive authentication method to users of mobile phones. As this authentication is no extra-work for the user but happens unnoticed to him, it is likely that more people would demand an authentication after a standby period. Biometric gait recognition based on accelerometer data is such an unobtrusive authentication method. When the owner of the phone is walking, the phone will recognize him based on his gait, so he can directly use the phone without any further authentication. When he is not walking, an alternative, active authentication method (e.g. PIN) can be used. In this paper, biometric gait recognition based on accelerometer data collected using the intrinsic sensors of the mobile device will be further explained and analyzed.

Different biometric characteristics such as fingerprints [1] already have been proposed to improve security of mobile devices. Biometric characteristics have the advantage that, unlike passwords, PINs, tokens etc., they cannot be stolen or forgotten. The main advantage of biometric authentication is that it establishes an explicit link to the subject's identity because biometrics use human physiological and behavioral characteristics. Most of these characteristics require an explicit user action when used for authentication, e.g. putting the finger on a fingerprint scanner. In contrast to this, our proposed method is unobtrusive because the relevant data is continuously recorded while the person is walking. These days many mobile devices already contain accelerometers that can be used to record the way a person walks.

Early studies from psychology [21], medicine [12] and biometrics [7, 14] already give evidence that human gait contains very distinctive patterns that can be used for identification and verification purposes.

All of the published studies on gait recognition using acceleration data use dedicated devices for data collection containing high-grade accelerometers. In contrast to this, we will describe in this paper the results on gait recognition when using data collected from a commonly available commercial mobile phone containing low-grade accelerometers. The particular type of mobile phone used in our research is the Google G1 phone [5] [1].

The rest of the paper is structured as follows: Section 6.2 gives an overview over different existing gait recognition techniques. Section 6.3 gives a description of the accelerometer embedded in the phone and in section 6.4 the used definitions are given. Section 6.5 describes the collection of gait data. In section 6.6 the methods applied for feature extraction are described and the results are given in section 6.7. Section 6.8 gives conclusions and in the last section (6.9) the future work is outlined.

6.2 Gait Recognition

The term *gait recognition* describes a biometric method which allows an automatic verification of the identity of a person by the way he walks. There are three different approaches in biometric gait recognition: Machine Vision Based, Floor Sensor Based and Wearable Sensor Based Gait Recognition.

In the machine vision approaches [20, 8, 13, 24], the system will typically consist of several digital or analog cameras with suitable optics for acquiring the gait data. Techniques such as background segmentation are used to extract features to identify a person. This technique is especially useful for surveillance scenarios.

In the floor sensor approach [11, 19], the sensors are placed on the floor which makes these methods suitable for controlling access to buildings. When people walk across the mat, they can be authenticated e.g. by the force to the ground which is measured by the mat.

The newest of the three approaches is based on wearing motion recording sensors on the body in different places: on the waist, in pockets, shoes and so forth. As our proposed method belongs to this group, it is explained in more detail here.

The wearable sensors (WS) can be accelerometers (measuring acceleration), gyro sensors (measuring rotation and number of degrees per second of rotation), force sensors (measuring the force when walking) etc. Table 6.1 gives an overview of current WS-based gait recognition studies from years 2004 to 2008. The last column, #TP, represents the number of test-persons.

All studies except Morris and Huang et al. were using only accelerometers for collecting the gait data and reported recognition rates based on the verification scenario. Morris and Huang et al. used other types of sensors including force sensors, bend sensors, gyro sensors etc. in addition to the accelerometer sensor.

The main advantage of gait recognition using accelerometers is that it provides an unobtrusive authentication method for mobile devices which already contain accelerometers

[1] Tanviruzzaman et al. [25] proposed a gait recognition model for a smart phone, and no experiment was performed.

Study	Sensor Location	EER	Recognition	#TP
Holien [9]	left leg (hip)	5.9 %, 25.8 %	-	60
Gafurov et al. [7]	ankle	5 %	-	30
Gafurov et al. [7]	trousers pocket	7.3 %	-	50
Gafurov et al [7].	hip	13 %	-	100
Gafurov et al. [7]	arm	10 %	-	30
Morris [17]	shoe	-	97.4 %	10
Huang et al. [10]	shoe	-	96.93 %	9
Ailisto et al.[4]	waist	6.4 %	-	36
Mntyjrvi et al. [14]	waist	7.0 % , 19.0 %	-	36
Rong et al. [22]	waist	6.7 %	-	35
Rong et al. [23]	waist	5.6, 21.1 %	-	21
Vildjiounaite et al. [27]	hand	17.2, 14.3 %	-	31
Vildjiounaite et al. [27]	hip pocket	14.1, 16.8 %	-	31
Vildjiounaite et al. [27]	breast pocket	14.8, 13.7 %	-	31

Table 6.1: Performance of current wearable sensor-based gait recognition systems. Modified from [7].

(like mobile phones, PDAs etc.). Therefore, it can be applied for continuous verification of the identity of the user without his intervention. This is a great advantage to other biometric systems like fingerprint or face recognition which are also suitable for implementation on mobile phones but require active user intervention. This advantage of accelerometer based gait recognition compensates the so far worse recognition rates. For example, the equal error rate (EER) of fingerprint recognition [2] or 2-dimensional face recognition [3], compared to gait recognition, achieve lower EERs.

As biometric gait recognition only works when the user is walking, this method has to be combined with another authentication method. In [26] Vildjiounaite et al. propose a cascaded fusion of gait, voice and fingerprint. The active authentication via fingerprint is only required when the two unobtrusive authentication methods fail. This happens in $10 - 60\%$ of the cases and indicates that adding an unobtrusive authentication method to mobile phones does decrease the neccessatity of regular active authentication and hence increases the user friendlyness.

6.3 Accelerometer

The G1 has an integrated sensor (AK8976A) for measuring acceleration in three axes [5]. This sensor is a piezoresistive MEMS (Micro-Electro-Mechanical-System) accelerometer which uses piezoresistors to measure the accelerations. Piezoresistors have the property that they change their resistance on tension and compression. The sensor consists of a cantilever beam which deflects from its neutral position under acceleration. This deflection is measured using piezoresistors. See Figure 6.1 for a schematic diagram of this principle [15]. Acceleration in all directions can be measured by combining three sensors perpendicular to each other such that they span the three-dimensional space.

6.4 Definitions

In the following we give the definitions used in this paper: A *go* starts when the recording of the data has been started and ends when recording has been terminated. In other words, everything stored in one file on the phone is one go, including attachment and detachment of the phone and the standing - turning around - standing at the end of the corridor. See section 6.5 for more details about data collection. Figure 6.2 shows the plot of one go. One

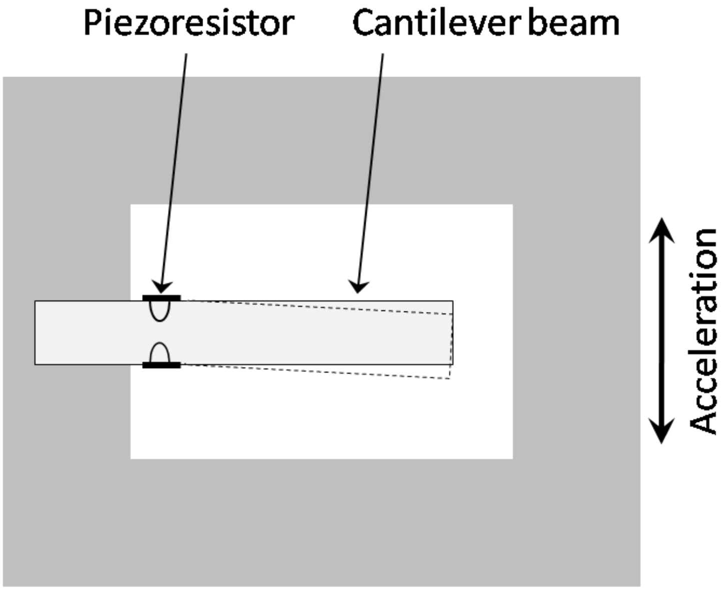


Figure 6.1: Schematic diagram of a piezoresistive accelerometer.

can see that two *walks* can be extracted from one go. One walk contains only data when the person is walking. It begins when the person starts walking and ends when he/she stops at the other end of the corridor. One walk contains several steps of one subject. There is a periodic repetition every two steps which is called one *cycle* [7].

6.5 Data collection

The data used in this article is collected using a standard G1 mobile phone which does contain accelerometers as described in section 6.3. The G1 uses the android platform and a software was written for this platform to access the accelerometer and output the data from the sensor to a file (40-50 samples per second for each of the three directions x, y and z). While recording the gait data the phone has been placed in a pocket attached to the belt of the subject on the right-hand side of the hip. The phone is positioned horizontal, the screen points to the body, the upper part of the phone points in walking direction (see figure 6.3).

The walking distance was about 37 meters down the hall on flat carpet (see figure 6.4). At the end of the hall the subjects had to wait 2 seconds, turn around, wait again and then walk back the same distance.

The subjects were told to walk as normal as possible, which means that different subjects can walk at different speeds.

In total 51 volunteers participated in the data collection (see table 6.2 for age and gender distribution). Each of them did two sessions at two different days wearing their normal shoes. From the data collected at each go, two walks could be extracted. One, when the subject was walking down the hall and the other one when he was walking back. So in total there are four walks for each subject.

The first walk was used to compute the reference template. The other three walks were used to compute the probe feature vectors, which were used for comparison.

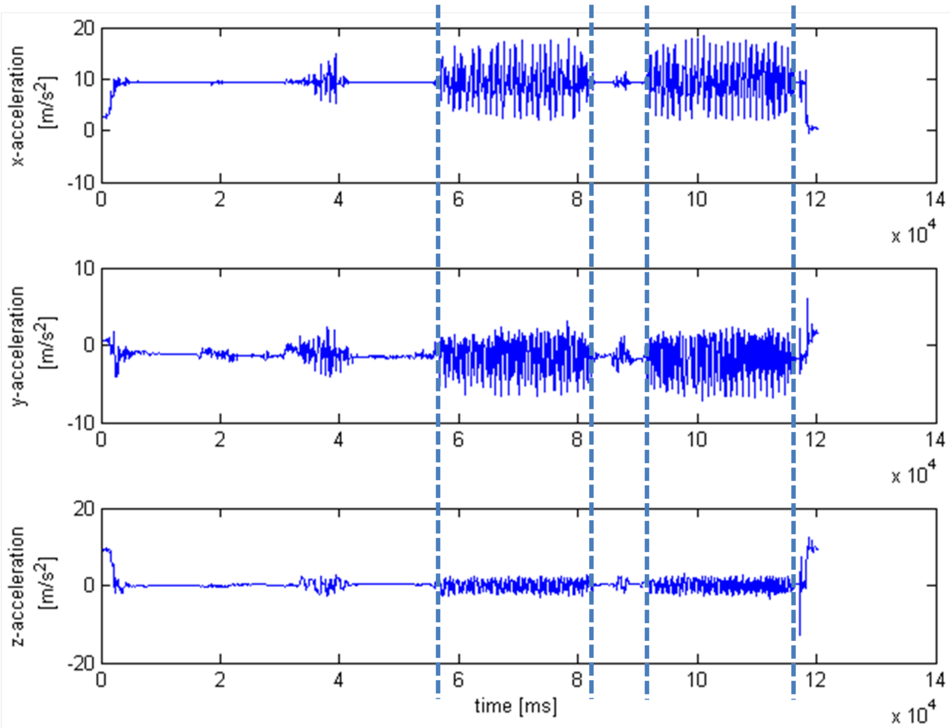


Figure 6.2: Sample data collected with the G1. The acceleration in x-, y- and z-direction collected during one go is shown, including attaching the phone etc. The dotted lines show the walking part of one go.

Figure 6.3: Phone attached to subject and the three axes in which acceleration is measured.

6.6 Feature Extraction

The raw data retrieved from the mobile phone needs to be processed in order to create robust templates for each subject. The program for data analysis has been developed in Java and is based on the work of [9]. Of the three different signals retrieved from the phone only the acceleration in x-direction is used as it showed to give the best results. From this raw data the repeating cycles are extracted to result in one single average cycle for each person. A brief description of the steps conducted for feature extraction is given in the following:

- *Time Interpolation:* Due to the android SDK, the phone only outputs data values when-

Figure 6.4: Photograph of the walking setting.

	< 20	$20-24$	$25-30$	> 30	unknown
male	1	2	26	10	2
female	0	5	4	0	1
total	1	7	30	10	3

Table 6.2: Age and gender distribution of volunteers.

ever there is a change in the sensor. Therefore, the time intervals between two sample points (acceleration values) are not always equal, which requires time interpolation. This ensures that the time-interval between two sample-points will be fixed.

- *Filtering:* Removal of noise is done by applying a weighted moving average (WMA) filter.

- *Average Cycle length:* From the data it is known that the cycle length is between $40-60$ samples. To compute the average cycle length a small subset from the center of the data is extracted and compared with other subsets of similar length. Based on the distance scores between these subsets, the average cycle length is computed.

- *Cycle Detection:* The cycle detection starts from a minimum point $P_{start} = P_{min}$ around the center of the walk. From this point, cycles are detected in both directions. By adding the average length to P_{start}, the estimated ending point $P_{end} = P_{start} + averageLength$ is retrieved (in opposite direction: $P_{end} = P_{start} - averageLength$). The cycle end is defined to be the minimum in the interval of +/- 10% (of the average cycle length) from the estimated end point, see figure 6.5. This process will be repeated from the new end point until all cycles are detected.

- *Average Cycle:* Before the average cycle is computed, irregular cycles are omitted. This is done by using Dynamic Time Warping (DTW) [18] to calculate the distances between all cycles and deleting the ones which have an unusual large distance to the other cycles. The cycle with the lowest average DTW-distance to the remaining cycles will be used as the average cycle. This average cycle, which is a vector (of real values) of an average length around 45 samples, will be used as the feature vector for this walk.

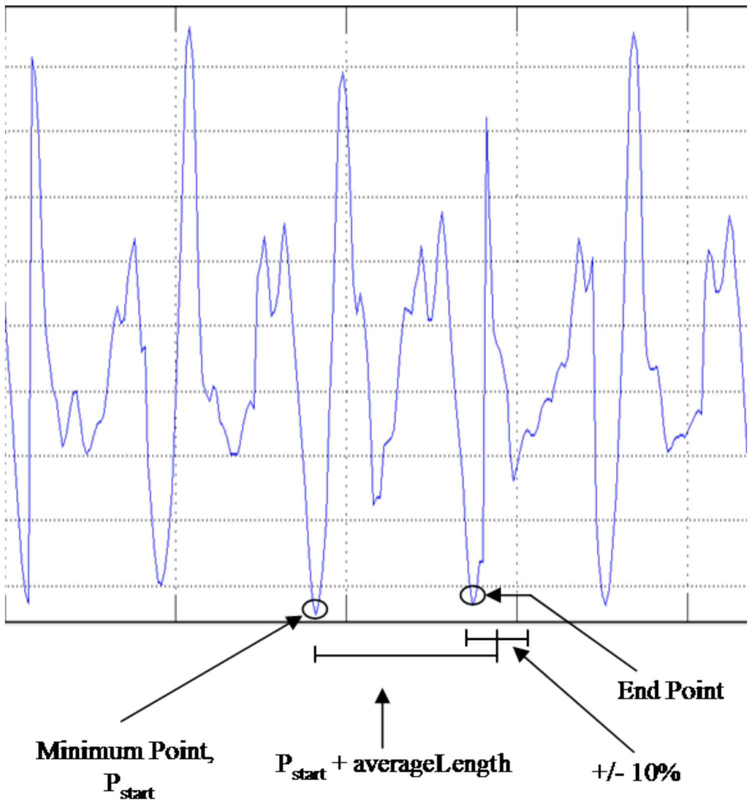


Figure 6.5: Cycle Detection

6.7 Results

The quality of the feature vector extracted as described in section 6.6 was analyzed. The distance metric used to compare two feature vectors was Dynamic Time Warping, which was chosen because the feature vectors by nature can have different lengths. By using DTW we avoid normalizing the feature vectors to a fixed length. The performance is measured in terms of False Match Rate (FMR) versus False Non-Match Rate (FNMR) and the results are graphically displayed using a DET (Detection Error Trade-off) curve in figure 6.6.

Comparing the achieved equal error rate of 20.1% to the error rate for the same analysis settings stated in Holiens work (12.9%) [9], one can see an increase of approximately 50%. An issue that needs to be taken into consideration is that the test data used in this paper was collected using a mobile phone which contains a lower sampling rate accelerometer. Its sample rate was around $40 - 50$ samples per second whereas the high quality dedicated accelerometer used in Holien had around 100 samples per second.

6.8 Conclusion

The main contribution of this paper was to demonstrate that one has the ability to use commercial mobile phones equipped with accelerometers to carry out biometric gait recognition. As stated before, the advantage of this method to other biometric systems which could be implemented on mobile phones, is the unobtrusive operation which gives a high user friendliness.

To the best of our knowledge, for the first time, data collected by accelerometers in a standard mobile phone was used for biometric gait recognition. A feature extraction

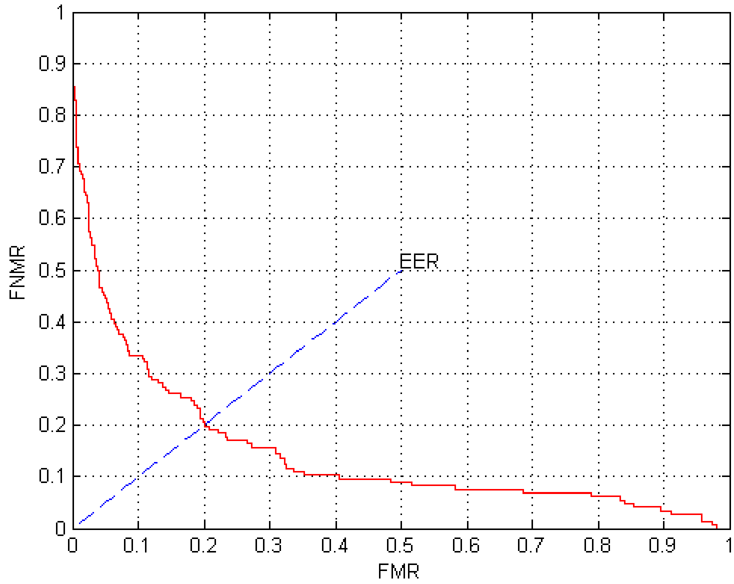


Figure 6.6: DET-curve: Performance of Gait Recognition with an EER of 20.1 %.

method was adapted and applied to the data from 51 volunteers collected in two sessions. The achieved EER of 20.1% is approximately 50% higher than the EER achieved with a similar method using a dedicated accelerometer with a twice as high sampling rate. To make biometric gait recognition using embedded accelerometers a technology suitable for practical use, further research on feature extraction and comparison is required. However the achieved results are promising and the proposed approach contains potential for enhancement.

6.9 Future Work

The obtained equal error rate of 20.1% indicates that biometric gait recognition can be run on mobile phones but it is not yet ready for practical use. Focus of our future work will be enhancing the cycle extraction technique to get more reliable feature vectors.

In addition to improving the recognition rates for normal walk on flat ground, future work will include analysis of different settings to create a gait recognition method which provides robust verification under different circumstances. These circumstances might be different walking conditions like walking speed or ground which will have an influence of the walk of a person and therefore might also influence the biometric recognition. Therefore, accelerometer data of the subjects will be recorded at several settings like different walking speeds and different grounds (e.g. carpet, grass, gravel).

In addition, data will be collected using phones at different positions (e.g. front and back trousers pocket and pocket attached to belt) for further analysis. To handle the movements of the phone when carried in a trousers pocket, values recorded by the magnetic field sensor can be used to normalize the orientation of the phone.

The attack resistance of biometric gait recognition should also be analyzed. Studies by Gafurov [7] and Mjaaland [16] show that it is difficult for an attacker to imitate another person. This needs to be confirmed for the special scenario of mobile phones.

6.10 Acknowledgments

We would like to thank all of our volunteers participating in the data collection and supporters. This work was supported by CASED (www.cased.de).

6.11 Bibliography

[1] Fingerprint solution to secure mobile phones. http://www.geekzone.co.nz/content.asp?contentid=1145. [Online; accessed 21-June-2010]. 95, 105

[2] FVC2006: the Fourth International Fingerprint Verification Competition. http://bias.csr.unibo.it/fvc2006/results/O_res_db2_a.asp. [Online; accessed 21-June-2010]. 97

[3] ABENI, P., BALTATU, P., AND D'ALESSANDRO, R. A face recognition system for mobile phones. *Information Security Solutions Europe 2006 Securing Electronic Business Processes* (October 2006), 211–217. 97

[4] AILISTO, H. J., LINDHOLM, M., MÄNTYJÄRVI, J., VILDJIOUNAITE, E., AND MÄKELÄ, S.-M. Identifying people from gait pattern with accelerometers. *In Proceedings of the SPIE - Biometric Technology for Human Identification II 5779* (2005), 7–14. 64, 65, 66, 67, 97, 108

[5] ANDROID DEVELOPERS. Accelerometer Documentation. http://developer.android.com/reference/android/hardware/ SensorEvent.html, 2009. [Online; accessed 21-June-2010]. 95, 96, 97

[6] CLARKE, N., AND FURNELL, S. Authentication of users on mobile telephones - a survey of attitudes and practices. *Computers & Security 24*, 7 (2005), 519 – 527. 95

[7] GAFUROV, D. *Performance and Security Analysis of Gait-based User Authentication*. Ph.D. thesis, Faculty of Mathematics and Natural Sciences, University of Oslo, 2008. xiii, 96, 97, 98, 102, 106, 108, 111, 112

[8] HAN, J., AND BHANU, B. Individual recognition using gait energy image. *IEEE Transactions on Pattern Analysis and Machine Intelligence 28* (2006), 316–322. 96, 107

[9] HOLIEN, K. Gait Recognition under non-standard circumstances, Master thesis, Gjøvik Univeristy College, 2008. 97, 99, 101, 106, 108, 112

[10] HUANG, B., CHEN, M., HUANG, P., AND XU, Y. Gait modeling for human identification. In *International Conference on Robotics and Automation* (2007), pp. 4833–4838. 67, 97

[11] JENKINS, J., AND ELLIS, C. S. Using ground reaction forces from gait analysis: Body mass as a weak biometric. In *Fifth International Conference on Pervasive Computing* (2007), pp. 251–267. 96, 107

[12] KALE, A. A. *Algorithms for gait-based human identification from a monocular video sequence*. Ph.D. thesis, College Park, MD, USA, 2003. 61, 96, 106

[13] LIU, Z., AND SARKAR, S. Improved gait recognition by gait dynamics normalization. *IEEE Transactions on Pattern Analysis and Machine Intelligence 28*, 6 (2006), 863–876. 96, 107

[14] MÄNTYJÄRVI, J., LINDHOLM, M., VILDJIOUNAITE, E., MÄKELÄ, S.-M., AND AILISTO, H. Identifying users of portable devices from gait pattern with accelerometers. *IEEE International Conference on Acoustics, Speech, and Signal Processing 2* (2005), ii/973 – ii/976. 63, 64, 65, 67, 96, 97, 108

[15] MIN-HANG BAO. *Micro Mechanical Transducers: Pressure Sensors, Accelerometers and Gyroscopes (Handbook of Sensors and Actuators)*, vol. 8. Elsevier Science, 2000. 97

[16] MJAALAND, B. B. Gait Mimicking - Attack Resistance Testing of Gait Authentication Systems, Master Thesis, Norwegian University of Science and Technology, 2009. 102

[17] MORRIS, S. J. *A shoe-integrated sensor system for wireless gait analysis and real-time therapeutic feedback*. Ph.D. thesis, Division of Health Sciences and Technology, Harvard University-MIT, 2004. 97

[18] MÜLLER, M. *Information Retrieval for Music and Motion*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2007, ch. 4 - Dynamic Time Warping. 100

[19] NAKAJIMA, K., MIZUKAMI, Y., TANAKA, K., AND TAMURA, T. Footprint-based personal recognition. *IEEE Transactions on Biomedical Engineering 47(11)* (2000). 96, 107

[20] NIXON, M. S., CARTER, J. N., NASH, J. M., HUANG, P. S., CUNADO, D., AND STEVENAGE, S. V. Automatic gait recognition. In *Biometrics Personal Identification in Networked Society* (1999), Kluwer, pp. 231–250. 96

[21] REESE, H. W., AND RODEHEAVER, D. Age-related declinces in motor control. In *Handbook of the Psychology of Aging*, C. J. Ketcharn and G. E. Stelmach, Eds., 5th ed. USA, 2001, pp. 333–335. 96, 106

[22] RONG, L., JIANZHONG, Z., MING, L., AND XIANG, H. Identification of individual walking patterns using gait accelleration. *In 1st International Conference in Bioinformatics and Biomedical Engineering* (2005), 543–546. 97, 108

[23] RONG, L., ZHIGUO, D., JIANZHONG, Z., AND MING, L. A wearable acceleration sensor system for gait recognition. *In 2nd IEEE Conference on Industrial Electronics and Applications* (2007), 2654–2659. 67, 97, 108

[24] SARKAR, S., PHILLIPS, P. J., LIU, Z., VEGA, I. R., GROTHER, P., AND BOWYER, K. W. The humanid gait challenge problem: Data sets, performance, and analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence 27* (2005), 162–177. 96, 106

[25] TAMVIRUZZAMAN, M., AHAMED, S. I., HASAN, C. S., AND O'BRIEN, C. epet: when cellular phone learns to recognize its owner. In *Proceedings of the 2nd ACM workshop on Assurable and usable security configuration* (New York, NY, USA, 2009), SafeConfig '09, ACM, pp. 13–18. Available from: `http://doi.acm.org/10.1145/1655062.1655066`. 96

[26] VILDJIOUNAITE, E., MÄKELÄ, S.-M., LINDHOLM, M., KYLLONEN, V., AND AILISTO, H. Increasing security of mobile devices by decreasing user effort in verification. In *Second International Conference on Systems and Networks Communications, 2007.* (Aug. 2007), p. 80. 97

[27] VILDJIOUNAITE, E., MÄKELÄ, S.-M., LINDHOLM, M., RIIHIMÄKI, R., KYLLÖNEN, V., MÄNTYJÄRVI, J., AND AILISTO, H. Unobtrusive multimodal biometrics for ensuring privacy and information security with personal devices. In *4th International Conference Pervasive Computing* (2006), pp. 187–201. 67, 97, 108, 113

Chapter 7

Improved Cycle Detection for Accelerometer Based Gait Authentication

Abstract

Over the last years, there has been an increasing research interest in the application of accelerometry data for many kinds of automated gait analysis algorithms. The need for more security on mobile devices is increasing with new functionalities and features made available. To improve the device security we propose an improved biometric gait recognition approach with a stable cycle detection mechanism and comparison algorithm. Unlike previous work on wearable gait recognition, which was based from simple average cycling methods to more complicated methods, this paper reports new techniques for which can improve the performance, by using simple approaches. Preprocessing, cycle detection and recognition-analysis were applied to the acceleration signal. The performance of the system was evaluated having 60 volunteers and 12 sessions each volunteer and resulted in an equal error rate (EER) of 5.7%.

7.1 Introduction

Mobility is in the future and the future is currently in the present. Today's personal devices, whether we are dealing with mobile phones, PDAs, iPads, etc. are being held or put into the pocket of the user. What we dont have time to do on computers or laptops, we do on these devices and this makes the everyday much easier. They are not only used for mere communication such as calling or sending text messages; these devices are also used in applications such as m-banking, m-commerce and e-mails which result in financial and private information being stored on the device. Thus the data on the device represents by far the more valuable asset than the pure hardware [1]. Therefore, the security risks related to ever-present mobile devices are becoming critical since a mobile device ending up in the wrong hands presents a serious threat to information security and user privacy. Most common, the protection on portable devices against unauthorized usage is based on a PIN, which is not always effective considering security and memorability aspects [21]. An additional difficulty with PIN-authentication is that it requires explicit action from the user who has to enter it before using the phone. In consequence many users deactivate the PIN-authentication.

This unattractive situation can be improved by exploiting the intrinsic sensors of a mobile device and applying an unobtrusive method for user authentication, which does not require explicit attention nor action of the user. Biometric gait recognition based on accelerometer data such an authentication method and will be further explained and analyzed in this paper.

Today, mobile devices implements other biometric equipments such as fingerprint sensors [2] to improve the security. And by using biometric characteristics instead of passwords, PINs, tokens etc., makes authentication more efficient since these characteristics are not to be stolen or forgotten. In addition, biometric authentication establishes an explicit link to the subject's identity because biometrics use human physiological and behavioral characteristics. Usually, most biometric characteristics require an explicit (obtrusive) user

Figure 7.1: Background segmentation for extracting the silhouette picture (subtraction).

action for authentication, e.g. swiping the finger on a fingerprint sensor. However, the proposed method here in this paper does not require an obtrusive action. Instead, we introduce an unobtrusive gait recognition mechanism, where data is continuously recorded while the subject is walking.

Previous studies from different aspects, psychology [18], medicine [10] and biometrics [16] [4] [14], already give proof for that human gait contains very distinctive patterns that can be used for identification and verification purposes.

All of the published studies on gait recognition using acceleration data were mainly based on dedicated sensor and in the same time slightly aware of fulfilling these issues at the very same time:

1. Automated gait recognition
2. Stable cycle detection mechanism
3. A rich and fast comparison algorithm (distance metric)

In [4], we see several different, but very simple cycle detection mechanisms that are not fully automated. This means a lot of fixed parameters are used for the dataset. However, [7] introduces an extended version of [4], making the cycle detection more automated, but a lot of complicated methods were performed. In contrast to these, we describe a new possible method to gain improved results using simple cycle detection with a simpler distance metric. The particular type of device which was used in our research was the MR100 sensor [20].

The rest of the paper is structured as follows: Section 7.2 gives an overview over different existing gait recognition techniques. Section 7.3 describes the collection of gait data. In section 7.4 the methods applied for feature extraction are described and the results are given in section 7.6. Section 7.7 concludes the paper and, finally, section 7.8 describes future work.

7.2 Gait Recognition

There are three different approaches in gait recognition: Machine Vision Based, Floor Sensor Based and Wearable Sensor Based Gait Recognition. These will be explained in the next paragraphs.

Machine Vision Based (MV) In the machine vision approaches, the system will typically consist of several digital or analog cameras with suitable optics for acquiring the gait data. Techniques such as thresholding to convert images into black and white; pixel counting to count the number of light or dark pixels; or background segmentation are used to extract features to identify a person. Figure 7.1 shows an example of the MV-based approach with processed background segmentation.

Earlier gait recognition studies have shown promising results. Sarkar et al. [19] did an experiment with 1870 gait datasets from 122 subjects and reported an recognition rate of 78% in an identification scenario. This was further improved to a rate of 90% by other

research [11] [5].
Most of the current gait recognition approaches are MV-based. The main advantage for this type of recognition compared to other biometric systems is that persons are captured unobtrusively from a distance. Even though MV-based gait analysis is not that precise as other biometrics, e.g. fingerprints, it is still useful for surveillance scenarios.

Floor Sensor based (FS) In the floor sensor approach the sensors are placed on a mat along the floor which makes these methods suitable for controlling access to buildings. When people walk across the mat, the force to the ground is measured, this is also known as the GRF (Ground Reaction Force). In a research from the University of Southampton [17], such a floor sensor for gait recognition was prototyped and is illustrated in Figure 7.2.

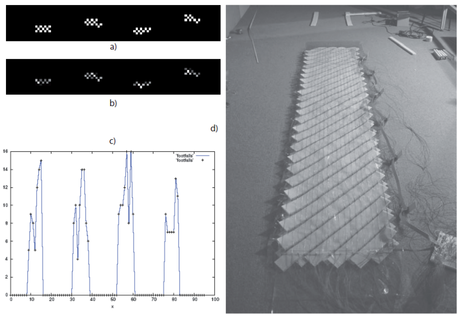


Figure 7.2: Gait collection by floor sensors. a) shows footsteps recognized, b) shows the time spent at each location in a), c) shows footstep profiles for heel and toe strikes, and finally d) is a picture of a prototype floor sensor carpet.

Their experiment had 15 subjects and three different features were extracted, namely the stride length (the distance traveled by the heel of one foot to the next time the same foot strikes down), stride cadence (the rhythm of a person's walk) and TOH ratio (the time on toe to the time on heel ratio). Using the TOH ratio an recognition rate of 80% could be achieved [15]. Different studies with small number of test persons (10 - 15) exist which report recognition rates up to 98.2%. Jenkins and Ellis [9] had 62 test persons and only reported a recognition rate of 39%.

Wearable Sensor based (WS) The wearable sensor recognition methodology is the newest gait recognition among the other mentioned earlier and that it provides an unobtrusive authentication method for mobile devices. This is based on wearing motion recording sensors on the body of the person in different places; on the waist, pockets, shoes and so forth.
The most common wearable sensors which are built-in into mobile devices are listed below:

- *Accelerometer Sensor:* Measures the acceleration .
- *Gyro Sensor:* Measures the rotation and number of degrees per second of rotation.
- *Force Sensor:* Measure the force when walking

Table 7.1 overviews the latest WS-based gait recognition research from years 2004 to 2010. The last column, #TP, represents the number of test-persons.

7.3 Data collection

The experiment was carried out on a solid surface. The 60 subjects who participated wore an accelerometer attached to a belt. The accelerometer was placed on the left leg, by the

Study	Sensor Location	EER	#TP
Gafurov et al. [4]	trousers pocket	7.3 %	50
Gafurov et al [4].	hip	13 %	100
Gafurov et al. [4]	arm	10 %	30
Gafurov et al. [3]	ankle	1.6 %	30
Holien [7]	hip	5.9 %	60
Ailisto et al.[6]	waist	6.4 %	36
Mntyjrvi et al. [8]	waist	7.0 % , 19.0 %	36
Rong et al. [12]	waist	6.7 %	35
Rong et al. [13]	waist	5.6, 21.1 %	21
Vildjiounaite et al. [22]	hand	17.2, 14.3 %	31
Vildjiounaite et al. [22]	hip pocket	14.1, 16.8 %	31
Vildjiounaite et al. [22]	breast pocket	14.8, 13.7 %	31

Table 7.1: Performance of current wearable sensor-based gait recognition systems.

hip. By attaching the accelerometer to a belt it ensured that the accelerometer more or less had the same orientation for all subjects. The subjects made the experiment over two days and were asked to walk as normal as possible in all 12 sessions, and to walk in a fixed length (20 meters). The subject walked the distance, and then stopped for three seconds, turn and wait, and then walk the same distance back. The accelerometer used was a Motion Recording 100 (MR100) sensor, with a sampling frequency of 100 samples per second and its dynamic range was between -6g and +6g (g = 9.8 m/s^2) for each of the three directions x,y and z.

7.4 Feature Extraction

The raw data retrieved from the MR100 sensor needs to be processed in order to create robust templates for each subject. The program for the gait data analysis has been developed in C#.

Preprocessing: The preprocessing is based on work from [4]. At first we apply *linear time interpolation* on the three axis data (x,y,z) retrieved from the sensor to obtain a observation every $\frac{1}{100}$ second since the time intervals between two observation points are not always equal. Another weakness from the sensor is the fact that the acceleration data will be outputted with some noise. This noise is removed by using a *weighted moving average*. Thereafter, the data values are converted to g-forces by using properties of the sensor. And finally we calculate the resultant vector or the so-called magnitude vector by applying the following formula,

$$r_t = \sqrt{x_t^2 + y_t^2 + z_t^2}, t = 1, ..., N$$

where r_t, x_t, y_t and z_t are the magnitudes of resulting, vertical, horizontal and lateral acceleration at time t, respectively and N is the number of recorded observations in the signal.

Cycle Detection: From the data it is known that one cycle-length varies between $80 - 140$ samples depending on the speed of the person. Therefore we need to get an estimation of how long one cycle is for each subject. This is done by extracting a small subset of the data and then compare the subset with other subsets of similar length. Based on the distance scores between the subsets, the average cycle length is computed, as can be seen in Figure 7.3.

The cycle detection starts from a minimum point, P_{start}, around the center of the walk. From this point, cycles are detected in both directions. By adding the average length, denoted γ to P_{start}, the estimated ending point $E = P_{start} + \gamma$ is retrieved (in opposite direction: $E = P_{start} - \gamma$). The cycle end is defined to be the minimum in the interval

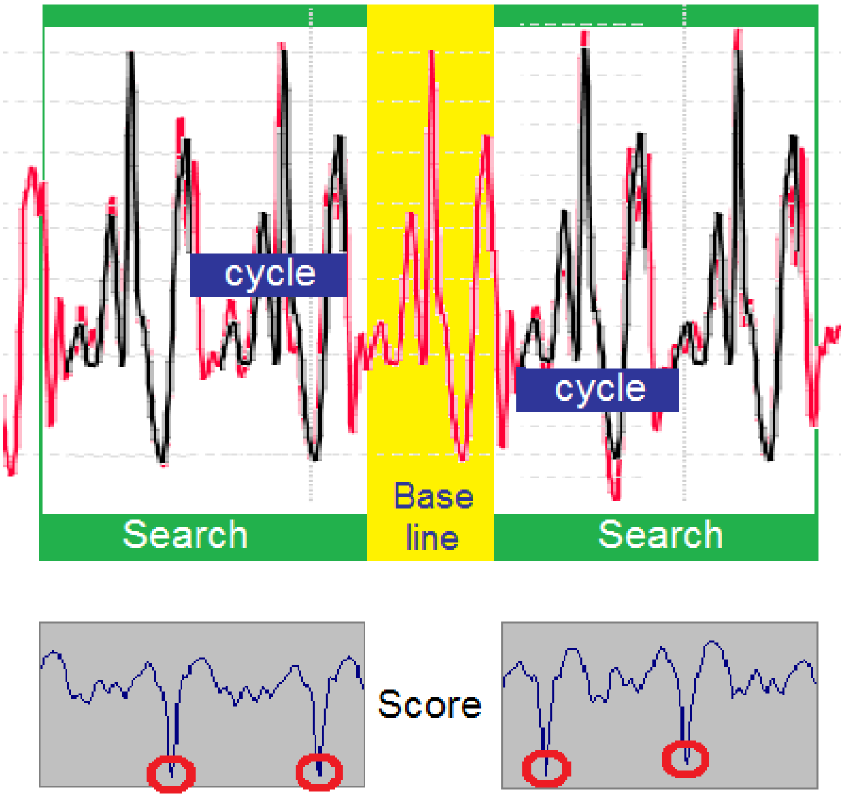


Figure 7.3: The yellow baseline area indicate the subset with 70 samples that are extracted, the green area is the search area where the baseline is compared against a subset of the search area. The 4 black subgraphs are the baseline at those points it has the lowest distance with the search area subsets, and the difference between them (blue area) indicate the cyclelength

Neighbour Search from the estimated end point. This is illustrated in Figure 7.4. This process is repeated from the new end point, until all cycles are detected. The end point in the Neighbour Search is found by starting from point E. From this point we begin searching 10% of the estimated cycle length, both before and after E for the lowest point. Now three things can happen

1) The lowest point was found in the first $\frac{1}{3}$ of the search area, in this case we might have skipped too many samples and will therefore search $\frac{\gamma}{10*2}$ more samples backwards. If a new lowest point was found we will continue to search additional samples backwards until no new lowest point is found, see Figure 7.5(a).

2) The lowest point was found in the last $\frac{1}{3}$ of the search area, in this case we might have skipped too few samples and will therefore search $\frac{\gamma}{10*2}$ more samples forwards. Like with the previous step, if a new lowest point was found we will continue to search forward until no new lowest point is found, see 7.5(b).

3) The lowest point was found in the middle $\frac{1}{3}$ of the search area, in this case we assume to have found the correct minimum point, see Figure 7.5(c). When the minimum point is found we store it into an array and we begin searching for the next minimum point by adding the length of one estimated cycle. When forward searching is complete we repeat this phase by searching backwards so all steps in the data are identified. We will therefore end up with having an array containing each steps start/end index. These points will therefore be used for the extraction of cycles, as illustrated in Figure 7.6.

Template Creation: Before we create the feature vector template, we ensure to skip cycles

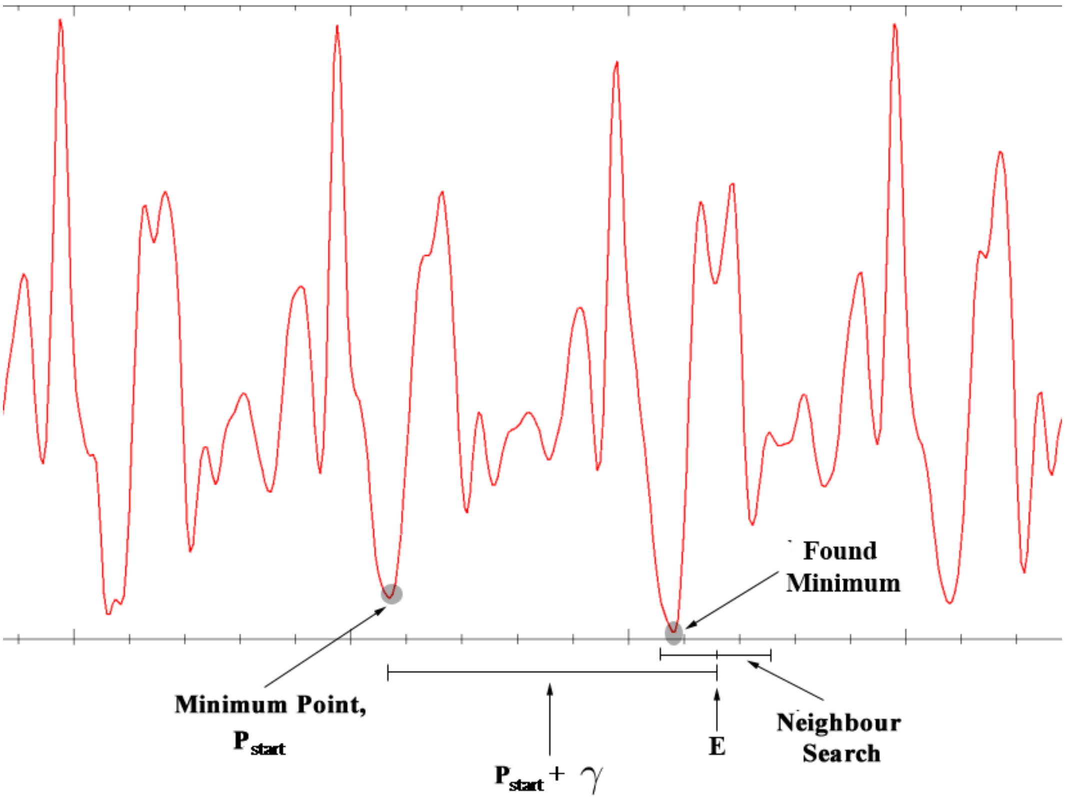


Figure 7.4: Cycle detection showing how each cycle (i.e the steps) in the resultant vector is automatically detected.

that are very different from the others. This is done by taking each cycle and calculate its distance to every other cycle by using dynamic time warping (DTW),

$$dtw_{i,j} = dtw(cycle_i, cycle_j)$$

where i = 1..N and j = 1..N, which means that we will get a symmetric N $\times$ N matrix. From this point, we calculate all the averages of one specific cycle to all others.

$$d_i = \frac{1}{n-1} \sum_{j \neq i} dtw_{i,j}$$

Thereafter we calculate the average of the calculated averages,

$$\mu = \frac{1}{n} \sum_i d_i$$

which therefore will be the total average. Now we will have the opportunity to see how much deviation one cycle differs from another. Thus, the standard deviation, μ, is calculated and to put a realistic border we will accept cycles that are within 2σ of difference from the total average

$$d_i = [\mu - 2\sigma; \mu + 2\sigma]$$

The 2σ is used to process trial and error. If a lower limit was chosen, we might had ended up skipping too many cycles, while a higher limit would lead to not skipping cycles we want to skip.

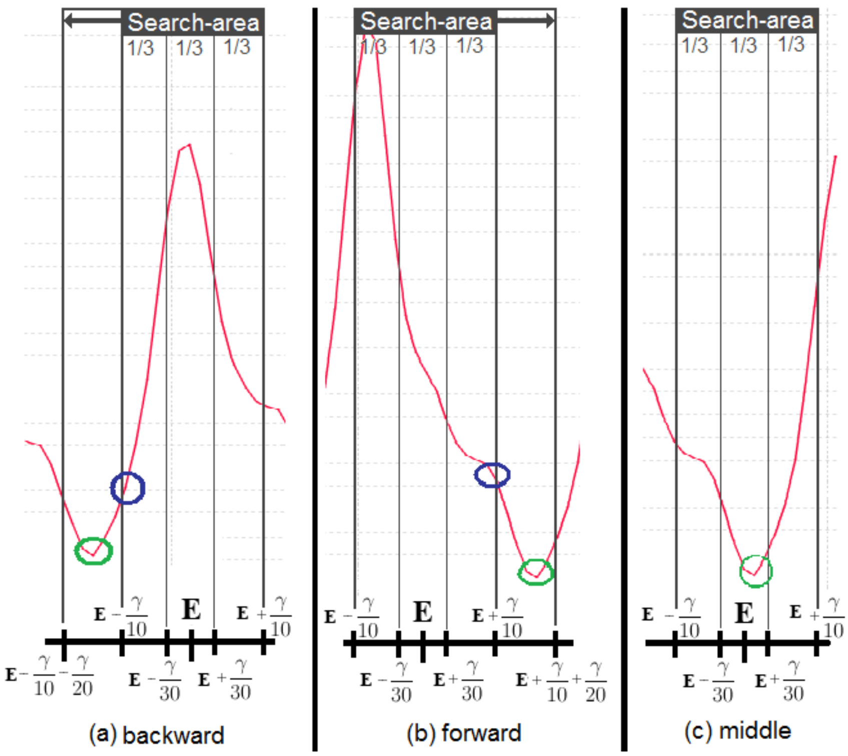


Figure 7.5: The Neighbour Search is illustrated for the three options that can happen when we are searching for steps, (a) we have jumped too far and since the lowest point in the search area (blue circle) is in the first third we search additional samples back and find the correct minimum point (green). (b) same as with the backward search only that we search forward this time since we have jumped too short. (c) we have jumped satisfactory and the correct minimum is in the middle third of our search area.

When all odd cycles are removed, we want to create the feature vector. In previous work, researchers used an average cycle as a feature vector. That was computed by combining all cycles (which were normalized) into one average median cycle [4]. In this paper we propose a method where all of the extracted cycles are stored as a template for one subject, denoted $C^S = \{C_1^S, ..., C_N^S\}$ where each cycle i = 1..N is normalized to a length of *k* observations; in our case *k = 100*. Eight to fifteen cycles were stored per session.

7.5 Feature Vector Comparison

A new distance metric, named the cyclic rotation metric (CRM), is proposed. This metric cross-compares two sets of cycles with a cyclic-rotation mechanism to find the best matching pair:

Cross Comparison: is used to find the most optimal and best distance score when cross-comparing two set of cycles, denoted $C^S = \{C_1^S, ..., C_N^S\}$ and $C^T = \{C_1^T, ..., C_M^T\}$. This simply mean that each cycle in set C^S is compared to every cycle in set C^T. The comparison distances are calculated by the cyclic rotation metric (CRM). From the total number of N $\times$ M similarity distance scores gained, the minimum distance score is selected,

$$d_{min} = min\{CRM(C_i^S, C_j^T)\}$$

where i=1..N and j=1..M. The pair of cycles with the most minimum similarity score is considered the best matching pair. Thus, this best (i.e. minimum) similarity score, d_{min}, is

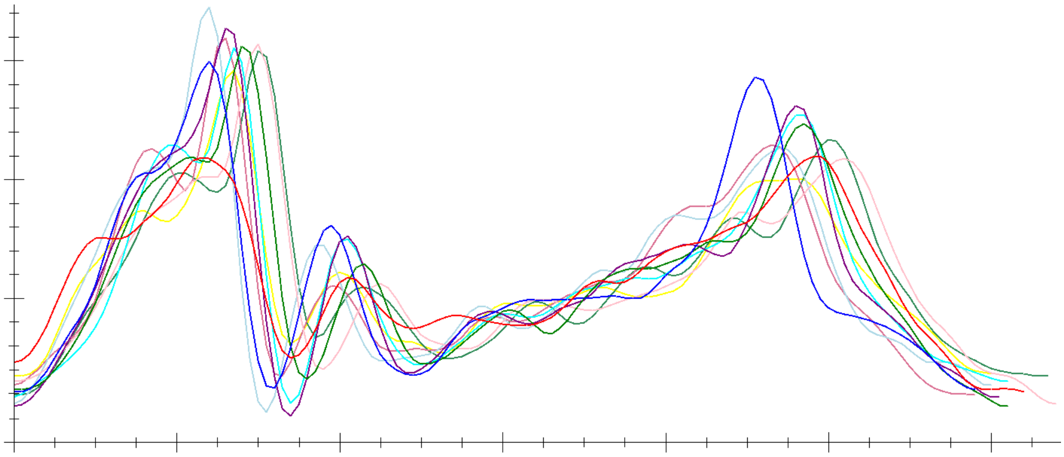


Figure 7.6: The cycles have been extracted by taking each steps starting and ending point. Both these points are minimum points from the resultant-vector data set.

used as the similarity score between set C^S and C^T.

Cyclic Rotation Metric (CRM): is a metric that compares a reference cycle and an input cycle with each other. The reference cycle, i.e. C_i^S, which is compared against the input cycle, i.e. C_j^T, is stepwise cyclical rotated. After each rotation the new distance is calculated using the manhattan distance. This is repeated until the input template has done a full rotation, then the lowest dissimilarity is kept:

$$d(C_i^S, C_j^T) = min_{w=1..k}\{Manh(C_i^S, C_{j(w)}^T)\}$$

, where $k = 100$. When having the two cycles with lowest manhattan distance, we then finally apply dynamic time warping on these cycles which then will be the final distance score

$$CRM(C_i^S, C_j^T) = DTW(d(C_i^S, C_j^T))$$

The reason why we calculate the manhattan distance when rotating and thereafter applying DTW when the minimal manhattan distance is found, is due to the fact that manhattan runs fast and linear, $O(n)$ while DTW is $O(n^2)$. And furthermore the cyclic rotation is done to minimize the problem when local extremes among the cycles we create for each input are located at different locations.

7.6 Results

Having 12 sessions for each person; that would give $\frac{12\cdot(12-1)\cdot 60}{2}$ = 3960 genuine attempts and $\frac{720\cdot(720-12)}{2}$ = 254880 impostor attempts. With these high numbers compared to trials presented in the papers from Table 7.1 we gain an increased performance with an EER = 5.7 %, see Figure 7.7.

From Table 7.2, we display the performances for three cycle detection methods. The

	Ours	Gafurov [4]	Holien [7]
Euclidean	8.2 %	13%	8.4 %
DTW	-	11.75%	5.9 %
CRM	5.7 %	-	-

Table 7.2: Comparison of various methods - Equal error rates (EER) are presented

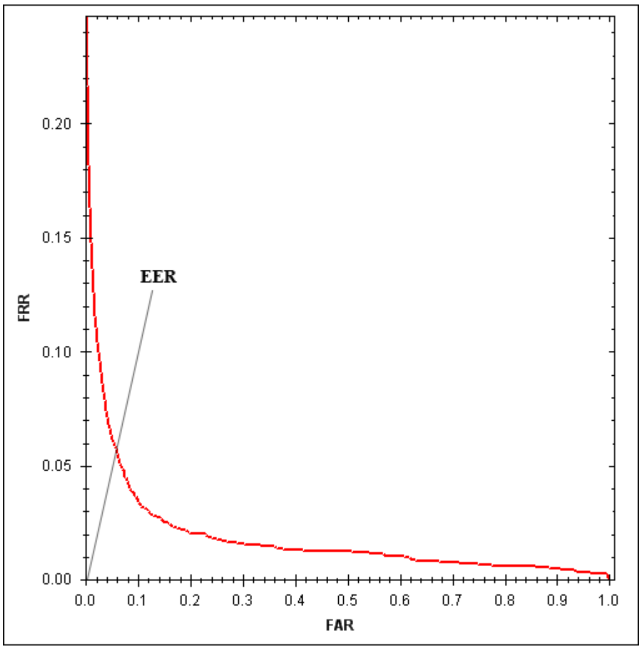


Figure 7.7: DET-curve: Perfomance of Gait Recognition with an EER of 5.7 %. The x-axis indicates the false acceptance rate (FAR) and y-axis indicitas the false rejection rate (FRR).

performance of our method is slightly more improved than Holien's and more than twice as good as Gafurov's.

Furthermore, Table 7.3 shows a more detailed overview that compares Gafurov et al. and Vildjiounaite et al. [22] who applied different approaches. However, there are still several similarities with our experiment and Gafurov et al.s experiment such as the use of same sensor and that the experiment was carried out in the exact same location. Holien uses the same settings as we do; therefore, it is not described in the table.

	Ours	Gafurov	Vildjiounaite
Sensor	MR100	MR100	ADXL202JQ
Sensor Placement	Left hip	Right Hip	Hip Pocket
Participants	60	100	31
Sessions	12	4	2
Algorithm	Cross	Average Cycle	Step Method
Ditance Metric	CRM	Euclidean	Correlation
EER	5.7 %	13%	14.1 %

Table 7.3: A table showing the main differences between our experiment and others.

7.7 Conclusion

This paper looks at interesting aspects of the biometric feature gait. A new, simple and rich gait recognition approach has been proposed. The proposed feature extraction method is adapted and applied to data from 60 volunteers. We can clearly say that we have achieved improved result with an EER of 5.7%, especially when we look at the number of participants and the genuine/imposter attempts. Even though that we had fewer participants than some of the other databases described in Table 7.1, we did have more recordings per participant, almost up to twice the number of gait sequences. Our achieved EER is at first, much lower than the EERs for accelerometer based gait recognition that was placed on the hip as seen in Table 7.1 and in section 7.6. Secondly, our algorithm is more rich and stable, meaning that we have developed and automated cycle-detection (Neighbour Search algorithm), and finally the comparison that finds the best and most optimal distance score from two feature vectors with the use of cross comparison and Cyclic Rotation Metric (CRM) as a distance metric.

7.8 Future Work

To make biometric gait recognition a technology suitable for practical use, using embedded accelerometers, further research on feature extraction and comparison is required. However the achieved result is promising and the proposed approach contains potential for enhancement. Different walking conditions like walking speed or ground might have an influence of the walk of a person and therefore might also influence the biometric recognition. Therefore, accelerometer data of the subjects will be recorded at several settings like different walking speeds and different grounds (carpet, grass, gravel). In addition, data will be collected using phones at different positions (front and back trouser pocket and pocket attached to belt) for further analysis.

In addition to improving the recognition rates for normal walk on different setting, we will in future work include analysis of the different settings mentioned before to create a gait recognition method which provides robust verification under different circumstances and especially begin analyzing acceleration data from a mobile phone.

7.9 Acknowledgments

We would like to thank all of our volunteers participating in the data collection and supporters.

7.10 Bibliography

[1] Biometrics for secure mobile connections. http://www.21stcentury.co.uk/technology/biometric for-mobiles.asp. [Online; accessed 19-June-2010]. 105

[2] Fingerprint solution to secure mobile phones. http://pagesperso-orange.fr/fingerchip/biometrics/types/fingerprint_products_ pdaphones.htm. [Online; accessed 19-June-2010]. 95, 105

[3] Davrondzhon Gafurov, E. S., and Bours, P. Improved gait recognition performance using cycle matching. In *International Conference on Advanced Information Networking and Applications* (2010). 108

[4] Gafurov, D. *Performance and Security Analysis of Gait-based User Authentication*. Ph.D. thesis, University of Oslo, Faculty of Mathematics and Natural Sciences, 2008. xiii, 96, 97, 98, 102, 106, 108, 111, 112

[5] Han, J., and Bhanu, B. Individual recognition using gait energy image. *IEEE Transactions on Pattern Analysis and Machine Intelligence 28* (2006), 316–322. 96, 107

[6] Heikki J. Ailisto, Mikko Lindholm, J. M. E. V. S.-M. M. Identifying people from gait pattern with accelerometers. *Biometric Technology for Human Identification II. In Proceedings of the SPIE 5779* (2005), 7–14. 64, 65, 66, 67, 97, 108

[7] Holien, K. Gait Recognition under non-standard circumstances, Master thesis, Gjøvik Univeristy College, 2008. 97, 99, 101, 106, 108, 112

[8] J. MANTYJARVI, M. LINDHOLM, E. V. S.-M. M. H. A. Identifying users of portable devices from gait pattern with accelerometers. *IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP '05) 2* (2005), ii/973 – ii/976. 63, 64, 65, 67, 96, 97, 108

[9] JENKINS, J., AND ELLIS, C. S. Using ground reaction forces from gait analysis: Body mass as a weak biometric. In *Pervasive* (2007), pp. 251–267. 96, 107

[10] KALE, A. A. *Algorithms for gait-based human identification from a monocular video sequence*. Ph.D. thesis, University of Maryland at College Park, College Park, MD, USA, 2003. Chair-Chellappa, Rama. 61, 96, 106

[11] LIU, Z., AND SARKAR, S. Improved gait recognition by gait dynamics normalization. *IEEE Transactions on Pattern Analysis and Machine Intelligence 28*, 6 (2006), 863–876. 96, 107

[12] LIU RONG, ZHOU JIANZHONG, L. M. H. X. Identification of individual walking patterns using gait accelleration. *In 1st International Conference in Bioinformatics and Biomedical Engineering* (2005), 543–546. 97, 108

[13] LIU RONG, DUAN ZHIGUO, Z. J. L. M. A wearable acceleration sensor system for gait recognition. *In 2nd IEEE Conference on Industrial Electronics and Applications* (2007), 2654–2659. 67, 97, 108

[14] MANTYJARVI, J., LINDHOLM, M., VILDJIOUNAITE, E., MAKELA, S.-M., AND AILISTO, H. Identifying users of portable devices from gait pattern with accelerometers. *Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP '05). IEEE International Conference on 2* (March 2005), ii/973–ii/976 Vol. 2. 106

[15] NAKAJIMA, K., MIZUKAMI, Y., TANAKA, K., AND TAMURA, T. Footprint-based personal recognition. *IEEE Transactions on Biomedical Engineeing 47(11)* (2000). 96, 107

[16] NIXON, M. S., TAN, T. N., AND CHELLAPPA, R. *Human Identification based on Gait*. International Series on Biometrics. Springer, 2005. Available from: `http://eprints.ecs.soton.ac.uk/11573/`. 61, 106

[17] OF SOUTHAMPTON, U. England. http://www.soton.ac.uk/. [Online; accessed 19-June-2010]. 107

[18] REESE, H. W., AND RODEHEAVER, D. Age-related declinces in motor control. In *Handbook of the Psychology of Aging*, C. J. Ketcharn and G. E. Stelmach, Eds., 5th ed. Academic Press, USA, 2001, pp. 333–335. 96, 106

[19] SARKAR, S., PHILLIPS, P., LIU, Z., VEGA, I., GROTHER, P., AND BOWYER, K. The humanid gait challenge problem: Data sets, performance, and analysis. *PAMI 27*, 2 (February 2005), 162–177. 96, 106

[20] SNDROL, T., AND SNEKKENES, E. Motion recording 100 sensor. http://www.motion-recording.com/pages/products/mr100.php, 2007. [Online; accessed 19-June-2010]. 106

[21] TANG, J., TERZIYAN, V., AND VEIJALAINEN, J. Distributed pin verification scheme for improving security of mobile devices. *Mob. Netw. Appl. 8*, 2 (2003), 159–175. 105

[22] VILDJIOUNAITE, E., MÄKELÄ, S.-M., LINDHOLM, M., RIIHIMÄKI, R., KYLLÖNEN, V., MÄNTYJÄRVI, J., AND AILISTO, H. Unobtrusive multimodal biometrics for ensuring privacy and information security with personal devices. In *Pervasive* (2006), pp. 187–201. 67, 97, 108, 113

Chapter 8

Scenario Test of Accelerometer-Based Biometric Gait Recognition

Abstract

The goal of our research is to develop methods for accelerometer-based gait recognition, which are robust, stable and fast enough to be used for authentication on mobile devices. To show how far we are in reaching this goal we developed a new cycle extraction method, implemented an application for android phones and conducted a scenario test. We evaluated two different methods, which apply the same cycle extraction technique but use different comparison methods. 48 subjects took part in the scenario test. After enrolment they were walking for about 15 minutes on a predefined route. To get a realistic scenario this route included climbing of stairs, opening doors, walking around corners etc. About every 30 seconds the subject stopped and the authentication was started. This paper introduces the new cycle extraction method and shows the Detection Error Trade-Off-curves, error rates separated by route-section and subject as well as the computation times for enrolment and authentication on a Motorola milestone phone.

8.1 Introduction

The development of mobile devices is progressing rapidly and constantly new features are added to the properties of the devices. These include high-quality cameras, UMTS-antennas, calendars etc. which increases the number of applications that can be run on the device and at the same time increases the amount of stored sensitive data. When smartphones are used in a business scenario, often confidential data like business contacts, emails, information about projects are contained in the devices. But also in a private environment the amount of sensitive data is high. Therefore, the protection of data stored on mobile devices is becoming more and more important.

While offering a large amount of applications, most mobile devices only offer one kind of authentication method which is knowledge-based (e.g. PIN or password). As studies have shown, these methods are not well accepted by the users [2]. Mainly out of convenience 87% of the users do not require PIN-authentication after a stand-by phase. As a result of this, all data stored on the device is freely available to any person gaining physical access to the device, which is clearly a security problem.

A solution to this problem is to offer alternative authentication methods which have a higher user acceptance. As many people who choose this low security setting do this because entering a PIN is too much effort, an alternative method should minimize the user interaction. We propose accelerometer-based gait recognition for authentication on mobile devices. As most smartphones already contain accelerometers (e.g. for games or adjusting the orientation of the screen), these can be directly used for recording of the gait data. No extra hardware is necessary, which is a great advantage over e.g. fingerprint recognition which can only be run on a few mobile phones containing fingerprint readers. However, the main advantage of gait recognition is its unobtrusiveness. While a subject is walking with his phone, the accelerometer data can be recorded. When the subject wants to use his phone after it was locked, the probe can be extracted and compared with the reference data stored on the phone. When there is no match the phone remains locked, otherwise the user can directly use it without having to enter any PIN or the like. In this case the user would notice no difference to an unsecured phone which shows the high usability of this method. To avoid false non-matches because of short irregularities in the gait (e.g. because of steps or irregular ground), the authentication decision should be based on data collected during a longer time period (e.g. 30 seconds). Clearly this method can not stand alone but has to be combined with some kind of active authentication like PIN, to allow an authentication in case the user is not walking.

Accelerometer-based gait recognition was first proposed by Ailisto et al. in 2005 [1] and further developed by Gafurov [6]. They used high-quality dedicated accelerometers which were placed on the hip, arm or ankle to record the acceleration while the subjects were walking. Only recently researchers started to use mobile devices to record the accelerometer data [4, 5, 7, 12]. Nevertheless, so far the feature extraction and comparison have always been executed on a PC and not on the device as done for this paper.

When introducing a new biometric authentication technique it is also important to consider the fraud resistance. The gait of a subject is visible to potential attackers who might analyze it to get access to the phone via mimicking. This was considered in a study by Mjaaland [10]. Despite having obtained feedback in the form of videos and statistical analysis, the participants did not show a significant improvement in learning a different gait. Although this study only includes a small number of subjects, it indicates that the possibility of mimicking gait does not have a big influence on the security of a gait recognition system.

The rest of the paper is structured as follows. The following section describes our mobile phone application which was used during the scenario test. Section 8.3 explains the newly developed method for cycle extraction. This method is used by the two different gait recognition methods described in section 8.4 followed by a description of the scenario test in section 8.5. The results are given in section 8.6 followed by a discussion in 8.7 and conclusions in 8.8.

8.2 Authentication System

As basis application for the tests we used our Modular Biometric Authentication Service System (MBASSy) which is described in more detail in [13]. This system was implemented for android phones and allows the integration of different authentication modules.

Different users can be registered in MBASSy and enroled for the active modules. Via the module settings it is possible to configure the duration of the data recorded during enrolment. After enrolment of a subject the reference templates are stored on the phone. The regular authentication procedure for our modules is as follows. By activating the screen saver the modules start collecting accelerometer data. When the screen saver is deactivated again (this happens normally when the user wants to utilize his phone) a lock screen is shown. During this, cycles are extracted from the data which was collected in the last 30 seconds and these cycles are then compared with the reference data. If the authentication result is true, the lock screen is closed and the phone can be used. Otherwise the lock screen offers the possibility to enter a PIN.

To minimize the time needed for each participant during the scenario test, this authentication procedure was changed. Instead of starting the cycle extraction we only store the so far recorded data on the phone when the screen saver is deactivated. Thus we separated the data collection from the processing and comparison. The described cycle extraction and comparison were performed afterwards on the phone. Therefore we augmented the mobile phone with a separate authentication application, which computed the dissimilarity distances, authentication results and times used for cycle extraction and comparison and stored them in an internal table on the phone. The advantage of this process is that data of all subjects are available during authentication and can be used to get impostor results. It was tested beforehand that the times computed using this separate application are comparable to the ones obtained using the regular authentication process.

8.3 Cycle Extraction Method

When using gait recognition on mobile devices in a realistic application scenario, a robust cycle extraction has to be used, which is able to handle irregularities occurring in the data. Former cycle extraction methods, which are mainly minimum (maximum) based, fail in case the gait data does not have distinctive minima (maxima). Our method addresses this problem by adapting the process depending on the data and using the salience vector (which is defined as the right salience vector in [9]) for determining where the cycles start [8].

The following subsections describe the conducted process which is illustrated in Fig. 8.1. Only acceleration measured in x-direction (vertical acceleration) is considered.

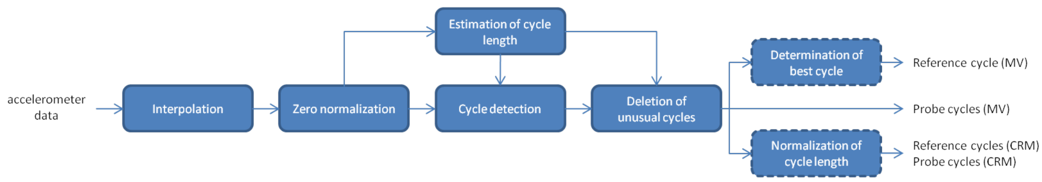


Figure 8.1: Flow diagram of the cycle extraction process. Only during enrolment for the majority voting module the step *Determination of best cycle* is applied. For the CRM module the cycles are normalized in length.

8.3.1 Interpolation

Due to constraints of the android API, the collected data does not have a fixed sampling rate. For further processing the data had to be interpolated to a fixed sampling rate. Using the Motorola Milestone® about 120 samples per second can be obtained. Using linear interpolation the data was transformed to have a fixed sampling rate of 150 samples per second.

8.3.2 Zero Normalization

The acceleration measured by the mobile device in a stable position (no movement) is not exactly zero (or gravity) and it is not stable over time. To reduce the influence of this property, the data is normalized around zero. This is done by subtracting its mean from the data.

8.3.3 Estimation of Cycle Length

To adapt the following cycle detection process, it is necessary to estimate the cycle length in advance. This is done by computing the min-salience and max-salience vector. The min-salience vector contains one entry for each data value. This entry is the number of data values which are between that data value and the following smaller one. This results in high entries in the salience vector in case the corresponding entry in the data vector is a significant minimum. The max-salience vector is created similarly but using the maxima.

Each entry of the salience vector which is greater than 120 (this is called a peak) and has a distance of at least 75 to the next peak is assumed to correspond to a cycle start. These parameters have been experimentally determined to give the optimal results. The more regularly spread maxima (lower standard deviation) are used for computation of the cycle length, which is the rounded mean value of the distances between neighboring peaks.

8.3.4 Cycle Detection

Cycle detection is also based on the salience vector. In many publications only the minima are used to identify the cycle start. Problems occur in case the minimum at cycle start is not greater than the minimum inside the cycle. In these cases often there are distinct maxima. As these maxima occur right at the beginning of the cycle they can be used to determine the correct minimum (cycle start).

The proposed method exploits this observation and computes the min-salience vector as well as the max-salience vector. The peaks of the salience vectors which have a minimum height of 105 (0.7*interpolation frequency) and a minimum distance of half the estimated cycle length are determined. In case of the min-salience vector these are used as initial cycle starts. In case of the max-salience vector the minimum before the detected maximum is used. To see whether the minima or maxima are more suited for calculation of cycle starts, the number of unusual long cycles (with length greater than 30 plus the estimated cycle length) is computed. The version which resulted in less irregular cycles is assumed to be the better one and the respective cycle starts are used.

The previously identified cycles that are too long, are further divided by again using the max- and min-salience vector. The identified additional cycle starts and the initial ones produce the set of cycle starts.

8.3.5 Omit Unusual Cycles

The cycles identified in the previous step are cleaned by deleting unusual cycles (see also [10]). The pairwise distance between all cycles is computed using dynamic time warping (DTW) [11]. The main advantage of DTW is that cycles do not have to be normalized in length before distance computation. Those cycles which have a distance of at least 50 to at least half of the cycles are deleted. Hereby is assured that there is always at least one cycle left.

For the majority voting module (see section 8.4.1) this is the last step during authentication and the remaining cycles are used as probe cycles.

8.3.6 Determine Best Cycle

In the majority voting module the cycles are further analyzed during enrolment. Similar to the previous step, the distances between all the remaining cycles are computed. The cycle for which the sum of the distance is minimal is the one which is most typical for the walk and hence is used as reference cycle.

8.3.7 Normalize Cycle Length

For the cyclic rotation metric module (see section 8.4.2) the cycles need to be normalized to an equal length. The reason for this is that the manhattan distance, which is used during cyclic rotation, can only be applied to vectors of same length. Thus, we normalize the remaining cycles from step 8.3.5 in time such that each cycle consists of exactly 100 acceleration values.

8.4 Gait Recognition Methods

Two different gait recognition methods have been implemented which are both based on the previously described cycle extraction, but use different comparison methods.

8.4.1 Majority Voting Module (MV)

This module uses the previously described method to extract cycles. During calculation of the probe cycles only steps 8.3.1 to 8.3.5 are executed and the remaining cycles are used as probe cycles. To calculate the reference cycles, during enrolment step 8.3.6 is also applied. Comparison is done using DTW as distance function and applying majority voting: The distances of the reference cycle to all probe cycles are computed. If the distance between two cycles is below a pre-selected threshold this is called a match, otherwise a non-match. If at least 50% of the results are a match, the whole comparision is assumed to be a match and the subject is authenticated.

8.4.2 Cyclic Rotation Metric Module (CRM)

The cyclic rotation metric module cross-compares two sets of cycles with a cyclic-rotation mechanism to find the best matching pair. The process is described in detail in [3] and what we observe here is that the CRM gives better performances than the usual use of euclidean, manhattan or DTW separately since it is always finding the optimal distance between two cycles. However, the CRM itself applies the last two mentioned distance metrics i.e., the manhattan distance and DTW. The metric works as follows: two normalized cycles are shifted 100 times and each time the manhattan distance is computed. If this distance is smaller than the so far computed minimal distance, the DTW-distance is also computed. At the end of the shifting process the minimum manhattan distance along with the corresponding DTW distance exists. This process is repeated for each combination of reference and probe cycle. The minimum of the resulting DTW distances and the corresponding manhattan distances is the final distance pair of this comparison. If at least one of these two distances is below the threshold the result is a match.

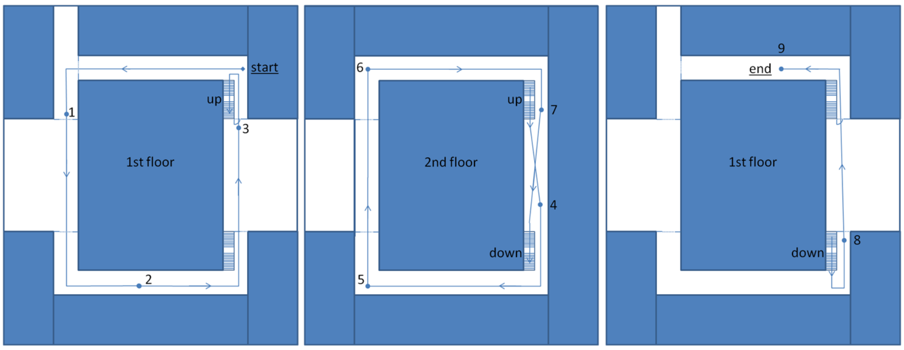


Figure 8.2: Subjects walked on this route. Authentication was started at the nine numbered points. Dashed lines indicate door sills.

8.5 Scenario Test

The goal of the scenario test[1] is to see how good the methods perform in a realistic scenario and if the time necessary to perform cycle extraction and comparison on a mobile device is acceptable. 48 subjects took part in our test. The mean age of the 18 female participants was 28.5 (minimum 20 years and maximum 53). The male participants were between 22 and 59 years old (mean age was 30.5 years). The participants were told to walk in their normal pace during the whole test. Each participant took part twice on two different days and in most cases was wearing the same shoes during both sessions. The phone was inside

[1]The target environment is an outdoor walking environment where a person will come in contact with other people and where there is a risk for a phone to be stolen. An example target environment could be a shopping street. The target environment can deviate from the test environment depending on the number of people and objects present making it less likely that the test person can walk in a straight line because he needs to avoid these other people and obstacle

a pouch which was attached to the right side of the hip of the subject. During each session we did the enrollment and authentication as described in the following sections.

8.5.1 Enrolment

As in each biometric system, the subjects had to be enrolled on the phone before the real test can start. For each module the subject had to walk 10 seconds straight on a flat floor. Depending on the module one or several reference cycles were computed from that data and stored on the phone. The computation times are stated in table 8.1. The longer time for the majority voting module is due to the additional step which selects the best cycle.

8.5.2 Data Collection

After enrolment the subjects had to walk on a predefined route three times. This route involved two floors of the institute which has a rectangular shape with a patio in the center, which allowed us to define a route without dead end (see Fig. 8.2). During walking on that route the subjects had to stop at nine predefined authentication points approximately 30 seconds apart from each other. In order not to influence them, the subjects were walking unattended. The route was chosen in such a way that it corresponds to a realistic scenario. Therefore it involved walking around corners, walking up and down stairs, opening and closing doors, having to cross door sills and walking on different surfaces (linoleum and tiles)[2]. For each of the 48 subjects and each module we obtained 27 data sets in each session, 2592 in total. Fig. 8.3 shows the data collected of one subject in section four. The part where the subject is walking downstairs is clearly visible in the right half of the figure. The file also contains the data where the subject was still standing. It is not further preprocessed but directly input to step one of the cycle extraction.

8.6 Results

To allow for a fair comparison of the two modules, it is necessary that the same data is used for calculation of the reference templates. Therefore we reconstructed the reference templates of the majority voting module by using the enrolment data of the CRM module. These reconstructed references are used in all following tests. Using the previously described authentication application probe cycles were extracted and compared to the reference data (see table 8.1 for mean times).

		CRM	MV
extraction of reference cycle(s)	min	1179	2135
	max	4823	4880
	mean	2381	3067
extraction of probe cycles	min	8758	7408
	max	65573	58021
	mean	26210	22843
comparison	min	920	84
	max	107628	1864
	mean	5685	372

Table 8.1: Mean times (in milliseconds) needed for cycle extraction and comparison.

For each subject and each module we have two reference templates, one for each session. An interesting point is to see the influence of the reference template and the influence of the time period between enrolment and authentication. Therefore we separated the data

[2] Appendix H describes more information on length and other characteristics.

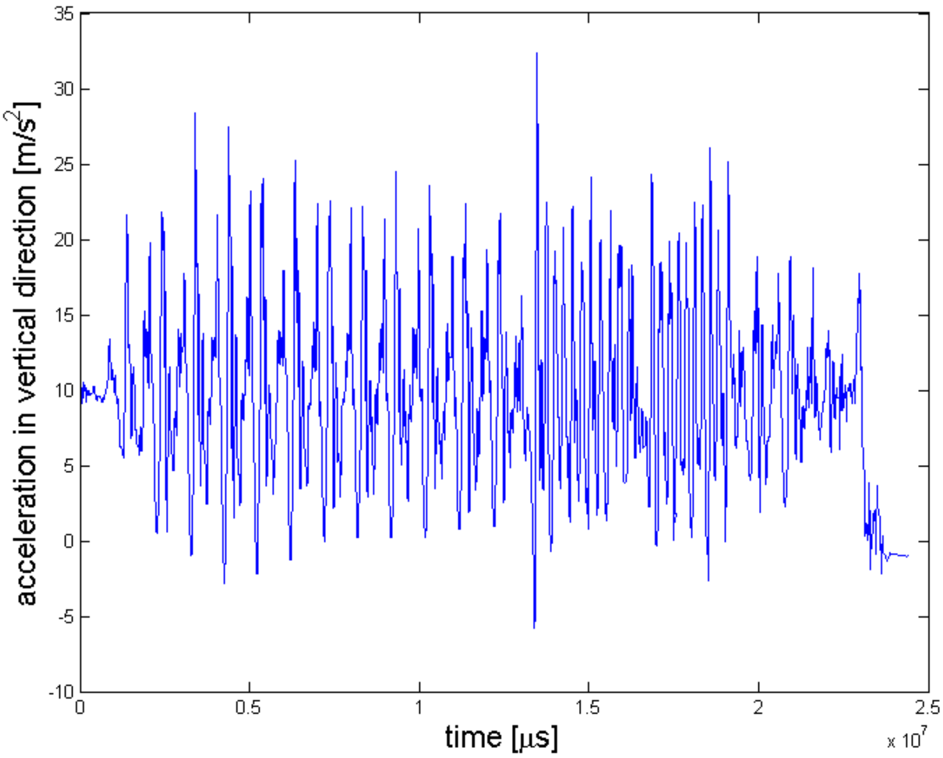


Figure 8.3: Sample data of section four in which the subjects also had to walk downstairs.

of the two sessions. Each reference template was compared with the data from the same session and the other session (on a different day). In Fig. 8.4 and 8.5 one can see the DET-curves. The thin red lines (R1Px) show the results when using the reference template recorded during the first session, the medium black lines (R2Px) show the results obtained with the reference template of the second session. The dotted lines (RxP0) show the same-day results, the continuous line (RxP1) the different-day results and the dash-dotted-lines (RxP2) show the result when data of both days is used for testing. The equal error rates can be seen from the crossing with the diagonal. One can clearly see that the error rates increase when enrolment and probe data are not from the same day.

The bold green lines (R3Px) correspond to the results obtained when using the best reference template. This is determined by computing the false non match rates using the same-day probe data. For each subject that template is chosen which has the lower number of false non matches. This process would in a real scenario correspond to a training phase: Several templates are computed during enrolment. The one which gives the best performance (in terms of false non match rate) during the same day is finally stored as the reference template. The continuous green line (R3P1) gives the most realistic results of all tests: A training phase ensures that a high-quality template is used as reference and this reference will in general be compared with data which is not collected on the same day. This means that for the CRM module we obtain a EER of 21.7% and for the MV module of 28.0%.

The results were further analyzed seperately for each section (see Fig. 8.6) and each subject (see Fig. 8.7). The given false non match rates are obtained at a false match rate of approximately 10% for each module, while using the previously determined best reference template and probe data of a different day. One can see that for both modules the false non match rates are nearly the same for all sections, only section 4 and 8 show worse results. The reason for this will be that these sections contain only two short walking parts, divided

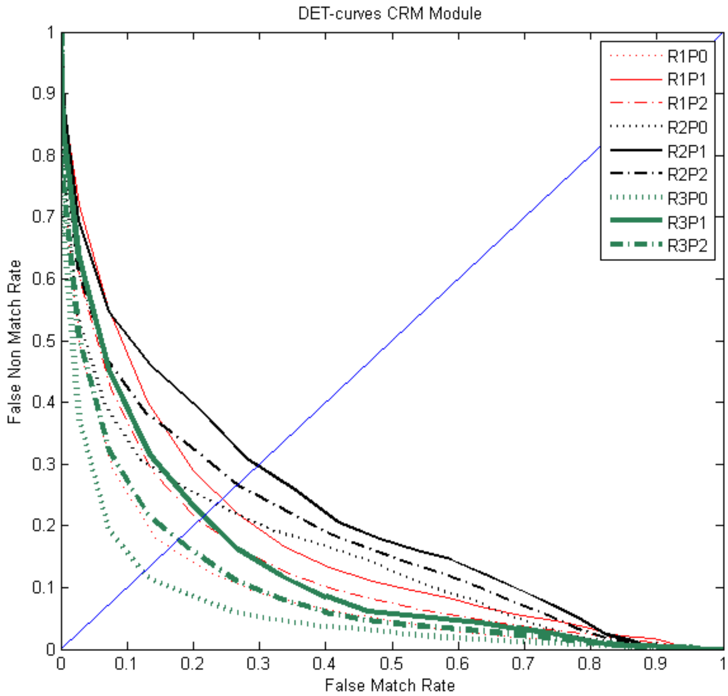


Figure 8.4: DET-curves for CRM method using different reference and probe data.

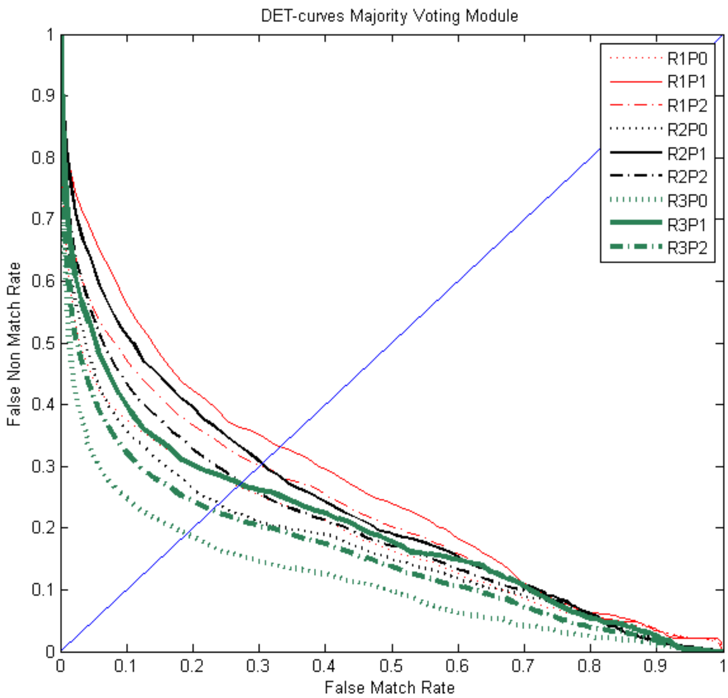


Figure 8.5: DET-curves for majority voting method using different reference and probe data.

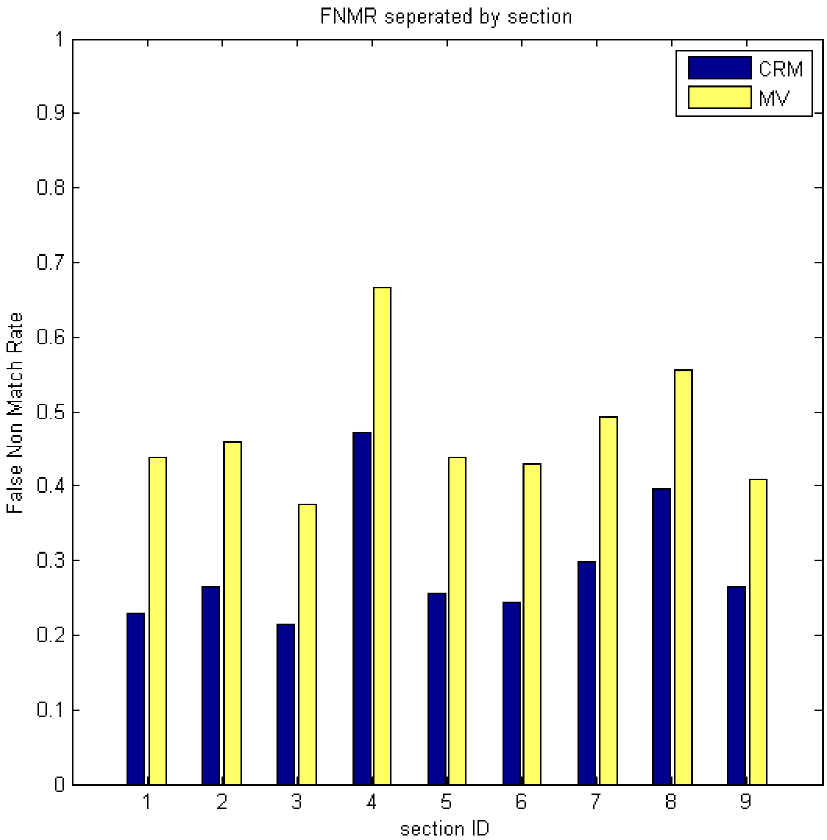


Figure 8.6: FNMR seperateted by section.

by the stairs. Fig. 8.7 shows that the authentication results greatly depend on the subject. Some subjects are never recognized, whereas some are always. One reason for this is that some subjects (8, 13, 15, 17, and 27) wore different shoes during the two sessions. For subject 8 and 13, the influence of the different shoes is not noticable, but it clearly is for the other three subjects.

8.7 Discussion

The conducted analyses had several goals:

- See how gait recognition performs in a scenario testing,
- determine which of the developed methods results in lower error rates,
- check if the modules perform fast enough on the phone.

For the realistic scenario of using the best (in terms of same day false non match rate) reference templates and comparing these with data collected on a different day, we got an EER of 21.7% for the CRM-module and of 28.0% for the MV-module. Fig. 8.7 shows that the recognition rates greatly depend on the subject. As already stated one reason could be the wearing of different shoes during the different sessions. Further influencing factors are the worn trousers which have an impact on the position (height, angle etc.) of the pouch as well as on how firmly it was attached. As a consequence, one can see that it is probably necessary that each subject does the enrolment several times using different trousers and

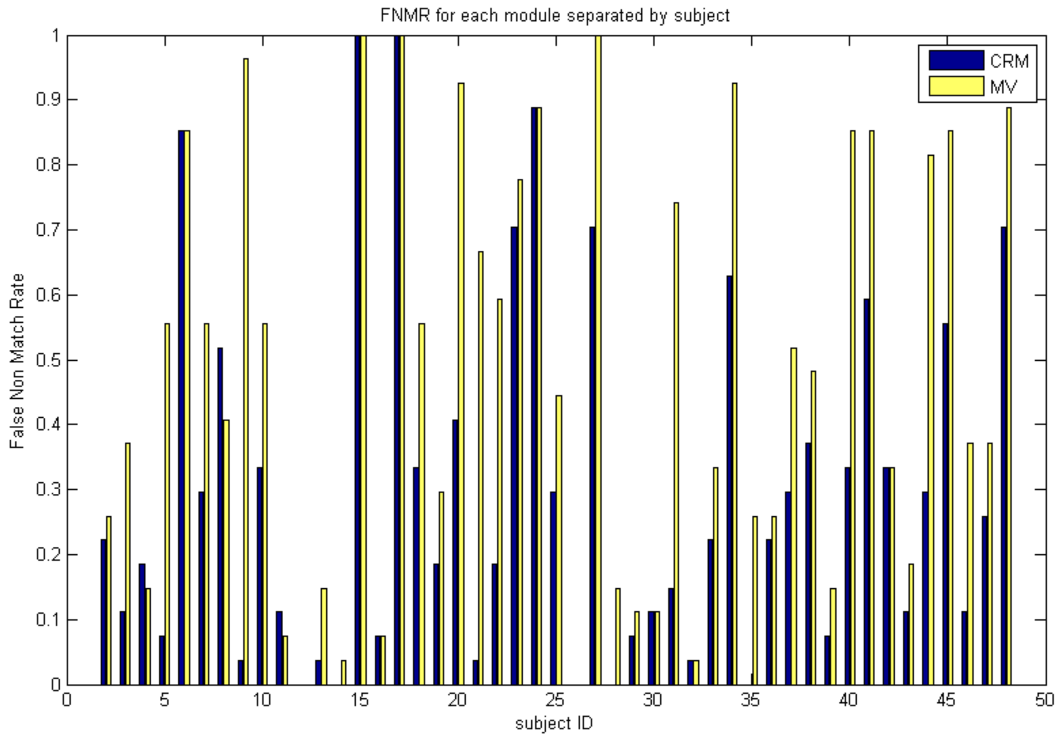


Figure 8.7: FNMR separated by subject (at a FMR of ca. 10%).

shoes. Adapting the threshold to the subjects would not be a suitable solution as a higher threshold makes it easier for attackers to get authenticated.

As one can see from the times given in table 8.1, extracting the probe cycles from data of one section and comparing these cycles with the stored reference cycle(s), takes around 32 seconds for the CRM-module and about 27 seconds for the MV-module. The longer computation time for the CRM-module is due to the length normalization of the cycles and the expensive cyclic rotation metric. These durations are far too high for a real authentication application, as a user would have to wait around half a minute until the phone unlocks itself, which is much more than entering a PIN would take. This situation could be improved by doing a continuous authentication. This means that the module collects 30 seconds of data, directly starts the authentications, stores the authentication result and starts collecting data again for the next 30 seconds and so on. The achieved recognition rates and times are good enough to implement this approach. When the user of the mobile phone starts the authentication, the last authentication result just needs to be obtained from memory, which could be done fast enough to be unnoticed by the user. With about 3 seconds for each module, the enrolment times are acceptable.

8.8 Conclusion and Future Work

In this paper a new cycle extraction method, based on salience vectors, was combined with two different comparison methods. The methods have been implemented for android phones and tested in a scenario test. On two different days each of the 48 participants walked for about 15 minutes on a predefined route which included 9 stopping points where the authentication data was stored. In contrast to previously conducted experiments, this route did contain corners, stairs, doors and door sills. Despite these obstacles, we obtained an equal error rate of 21.7% for the module using cyclic rotation metric as a distance and of 28.0% for the module using majority voting. Although these results are not as good as the results stated in many related papers, these are closer to reality. One reason is the more realistic data collection (not only flat floor) the other reason is that the stated EERs are obtained when comparing probe data of one day to reference data of a second day. We showed that this time difference has a great impact on the recogntion rates, which is seldom considered in literature.

Future work will include the conversion of the modules to applying continuous authentication. So far the authentication is started only once when the user wants to use his phone again and switches off the screen saver. As extracting cycles from 30 seconds of data and doing the comparison with the reference template takes about 30 seconds at the moment, this is not user-friendly. Alternating phases where data is collected with those where the cycle extraction and comparison is done and always storing the most current authentication result will improve this situation as only that result has to be obtained from the database. Adding this enhancement, the CRM-module can be used as a supplement to PIN authentication on mobile phones.

Acknowledgment

This work was supported by CASED (www.cased.de). The authors would like to thank all participants of the data collection.

8.9 Bibliography

[1] AILISTO, H. J., LINDHOLM, M., MNTYJRVI, J., VILDJIOUNAITE, E., AND MKEL, S.-M. Identifying people from gait pattern with accelerometers. *Biometric Technology for Human Identification II 5779*, 1 (2005), 7–14. VTT Electronics, Finland. 118

[2] BREITINGER, F., AND NICKEL, C. User Survey on Phone Security. In *BIOSIG 2010 - Proceedings of the Special Interest Group on Biometrics and Electronic Signatures* (2010). 117

[3] DERAWI, M. O., BOURS, P., AND HOLIEN, K. Improved Cycle Detection for Accelerometer Based Gait Authentication. In *Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing* (2010). 121

[4] DERAWI, M. O., NICKEL, C., BOURS, P., AND BUSCH, C. Unobtrusive User-Authentication on Mobile Phones using Biometric Gait Recognition. In *Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing* (2010). 118

[5] FRANK, J., MANNOR, S., AND PRECUP, D. Activity and gait recognition with time-delay embeddings. In *AAAI Conference on Artificial Intelligence* (2010). 118

[6] GAFUROV, D. *Performance and Security Analysis of Gait-based User Authentication*. Ph.D. thesis, Faculty of Mathematics and Natural Sciences, University of Oslo, 2008. 118

[7] KWAPISZ, J., WEISS, G., AND MOORE, S. Cell phone-based biometric identification. In *Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on* (2010), pp. 1 –7. 118

[8] MALOZEMOFF, A. Accelerometer-based gait recognition. Tech. rep., McGill University, 2009. 119

[9] MERTENS, C., GRENEZ, F., AND SCHOENTGEN, J. Preliminary evaluation of speech sample salience analysis for speech cycle detection. In *Proceedings 3rd Advanced Voice Function Assessment International Workshop* (May 2009), pp. 29–32. 119

[10] Mjaaland, B., Bours, P., and Gligoroski, D. Walk the walk: Attacking gait biometrics by imitation. In *Information Security*, M. Burmester, G. Tsudik, S. Magliveras, and I. Ilic, Eds., vol. 6531 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, 2011, pp. 361–380. 118, 120

[11] Müller, M. *Information Retrieval for Music and Motion*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2007, ch. 4 - Dynamic Time Warping. 120

[12] Sprager, S. A cumulant-based method for gait identification using accelerometer data with principal component analysis and support vector machine. In *Sensors, Signals, Visualization, Imaging, Simulation and Materials* (2009), pp. 94–99. 118

[13] Witte, H., and Nickel, C. Modular Biometric Authentication Service System (MBASSy) . In *BIOSIG 2010 - Proceedings of the Special Interest Group on Biometrics and Electronic Signatures* (2010). 118

Chapter 9

Towards an Automatic Gait Recognition System using Activity Recognition (Wearable Based)

Abstract

The need of increasing the security measures in mobile devices has led researchers focus on finding new security mechanisms. In this paper we propose a solution to keep data secured by ensuring that only the authorized user can access the data in a mobile phone. By using gait recognition as an important element for the authentication process we propose an automatic gait recognition system to be used for continuous authentication. Since recent gait recognition research only focuses on manual extraction of walking activities from the accelerometer signal, a solution to this issue could be activity recognition that would reduce the disadvantages of gait recognition by identifying the activities of a person continuously and automatically. Activity recognition would not only make it possible to authenticate the user in different daily activities like slow walking, normal walking, fast walking even running, but also help in avoiding authentication when the user is in passive state like sitting, standing still, etc.. This is one of the key factors and an interesting challenge which would benefit the data security area.

9.1 Introduction

In recent years, activity recognition has become a very important field of research due to its application in many different areas such as health care, fitness, industrial application, security, entertainment, etc.. The goal of activity recognition is to recognize and track human activities, which is also an important goal of ubiquities computing [21]. Computers are becoming more pervasive in modern society by integrating in our phones, music players, cars etc.. The idea of ubiquitous computing is to integrate computers into our environment, everyday objects and activities etc., to become assistance in our everyday lives and work [25].

Today, whenever we use computer systems, they demand authentication as a measure of security. Typically, we perform the authentication at login time with either a password, token, biometric characteristic and/or a combination of these. Performing the last mentioned measure is a stronger guarantee that the claimed user logging in is not an impostor but an authorized user. An issue raises that not many systems of security requires any further measures once the user is granted access (thus assuming that the user is continuously legitimated into the system). Continuous authentication insurance of the user's legitimacy is of high importance in critical or high security environments, this means that it is necessary to continuously ensure that the user is the legitimated one. Therefore, performing the user authentication continuously while the system is actively used is something essential. Nevertheless, this kind of authentication needs to be "attractive" for the user. A very good solution for continues authentication is activity recognition from the gait signal.

The latest generation of mobile devices (smart phones, PDA etc.) are more sophisticated and they come with built-in sensors like accelerometers, gyro-scopes, Global Positioning

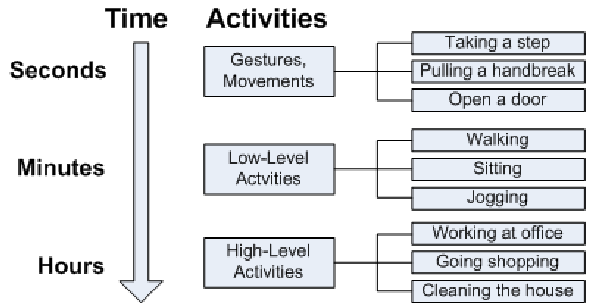


Figure 9.1: Level of Activitities [25]

Systems (GPS), etc., for example accelerometers can record the motion of the body and provide sufficient data that can be used for recognizing activities. Thus, accelerometers are becoming a very important tool due to good results in activity recognition: they are cheap, small, effective, require little energy, they are not sensitive on the conditions of the environment etc.. Because of these advantages of accelerometers they are incorporated in newer mobile devices, e.g. the iPhones, iPod, iPad, HTC etc..

This paper is divided into three sections. Section 9.2 gives an elaborate study related work overview on activity recognition to be used for gait recognition. Although gait recognition is not mentioned in this paper, an extensive survey of gait recognition can be found in [16]. Section 9.3 proposes a solution for a full automatic wearable based gait recognition system. Finally, Section 9.4 concludes the paper.

9.2 Activity Recognition - Related Work

Activity recognition is the process of identifying everyday common human activities in real life. It is a new area of study, and is becoming an interesting research field due to different areas of application. Accelerometers come integrated on new models of mobile devices such as smart phones, tablet computers, digital audio players (Ipod) etc., which record the body motion. The majority of studies for activity recognition are performed by using wearable sensors. Several studies have shown that wearable sensors are adequate for activity recognition. In the following we will show some of the sensors that have been used so far for activity recognition, a summary of different activities that were recognized by using various sensors and the approaches used for identifying different human activities.

Due to many different application areas of activity recognition, there is no surprise that the list of activities that many researchers have tried to recognize with various sensors is long. According to [25], activities can be categorized in three groups based on duration and/or complexity: *Gestures (or Movement/Motif)*, *Low-Level Activities*, and *High-Level Activities*. Activities such as walking, sitting, standing, eating, cleaning windows are considered as low-level activities which usually last between seconds and several minutes. As high-level activities are considered activities like sightseeing, cleaning the house, working at office, that usually last for more than a few minutes up to a few hours. Figure 9.1 illustrates these groups of activities.

9.2.1 Experiments (Activities)

The identification of everyday routine and leisure activities such as walking, running, biking, sitting, climbing and lying have already been analyzed in laboratory settings by several researchers. All these studies were done by different sensors such as accelerometers which were embedded in wearable sensing devices to collect the needed data. The types of sensors used for activity recognition are to be discussed in the next section. Accelerometer sensors are very useful for low-powered equipments like smart phones, tablet computers with applications that are suitable for real-time detection of user's activities. Physical activities such as walking, walking up/down stairs standing, sitting, and running have been studied by some of the researchers using different accelerometers sensors. Table 9.1 summaries different activities by different studies.

Table 9.1: Activity recognition research studies. #TP = Test Persons

Study	Activities	#TP
[68]	walking flat, walking slope-up, slope-down, walking stairs	52
[36]	sitting, walking, jogging, walking stairs, standing	29
[48]	sitting, standing, and walking	26
[45]	walking, running, cycling	24
[4]	walking, running, sitting, standing, bicycling	20
[13]	walking, climbing stairs	15
[19]	lying down, sitting and standing, walking, running,	12
[40]	sitting, standing, walking, walking stairs, riding elevator up/down, and brushing teeth	12
[21]	running, still, jumping and walking	11
[9]	sitting, walking, walking (street), waiting at a tram stop, riding a tram	8
[49]	walking, standing, sitting and running, walking stairs	6
[33]	sitting, walking, running, walking stairs	6
[74]	standing, walking, running, climbing	5
[22]	standing, sitting, lying, walking, running	5
[41]	sitting, walking, jogging, riding a bike, walking stairs	2

Another class of activities, mainly studied in healthcare environments, are the so-called "Activities of Daily Living" (ADLs). ADLs include activities such like bathing, toileting, dressing, feeding ourselves, homemaking which are basic skills needed for daily self-care activities. A set of ADLs is known as the "Instrumental Activities of Daily Living" (IADLs), those are skills beyond basic self-care which a person needs to perform for an independent living. IADLs include activities like shopping, driving, cleaning, cooking, doing laundry and managing money. Table 9.2 shows an overview of these activities.

9.2.2 Data Acquisition

Depending on the activities there have been used several kinds of sensors in the data acquisition process for activity recognition. As mentioned earlier, accelerometer sensors are adequate and most commonly used for continues activity recognition. They are also considered to be less intrusive than other sensors such as RFID gloves, microphones, and cameras [25]. Therefore, accelerometers are becoming very important tools due to many advantages in activity recognition. There is not a single sensor that can record all the body movements and recognize all kind of human everyday activities at one time. Therefore, most researches

Table 9.2: Studies of activity recognition of daily living (ADL)

Study	Activities (ADL)	#TP
[58]	toileting, washing, housework, leisure activity, oral hygiene, heating use, taking medication, etc.	14
[63]	mopping, cleaning windows, making bed, watering plants, washing dishes, setting the table, vacuuming, ironing, dusting	12
[19]	lying, rowing, cycling (training,regular), sitting, standing, running, walking, football	12
[52]	prepare food, clean dishes, wash clothes	10
[12]	showering, urination, flushing, washing Hands, defecation, brushing teeth	4
[65]	prepare food, toileting, bathing, dressing, grooming, preparing a beverage, doing laundry, etc.	2
[69]	prepare different food, eat cereal, dust, brush teeth, tend plants, set table, clean windows, take medication, shower, shave	2

today have been using different sensors to capture the data and multiple sensors attached on multiple parts of the body such as, hip, wrist, arm, ankle, chest, thigh, knee. For instance, activities like walking fast, walking slow, and running can be recognized by motion sensors but these sensors can not recognize activities such as, talking, reading, driving car etc.. Table 9.3 overviews some of the most widely used sensors for activity recognition research.

Other sensors that have been used for activity recognition are: GPS sensors [19], vision sensors (i.e., cameras) [19, 54], microphones [12, 29], RFID tag readers [56, 58, 63], ball switches [38], fibber optical sensors [18], gyroscope [35], body and skin temperature sensors [66, 43, 34, 76, 19], light sensors [66, 43, 49, 59], foam pressure sensors [8], pressure sensors [43], physiological sensors [55], humidity and barometric sensors [43].

9.2.3 Activity Recognition Process

9.2.3.1 Segmentation

Detection of activities from the collected data is the process of finding the "boundaries" for different activities in the accelerometer signal. Segmentation is a necessary step in the data analysis process before the feature extraction and the classification. Several segmentation techniques have been used to identify different activities from the sensor data. Some of the segmentation methods that have been used for activity recognition are: "Sliding Windows", "Top-Down", "Bottom-Up" and "Sliding Window and Bottom-Up (SWAB)" [31].

9.2.3.2 Feature Extraction

The input data recorded with the sensors from the human body motions is too large for processing, thus it is easier as an initial step to transform the large input data into a reduced representation set of features before further processing. The process of transforming the large input data into the set of features is called feature extraction. The feature extraction is

Table 9.3: Sensors used in different studies.

Study	Sensor Placement	Sensor
[32]	Above ankle, above knee,hip, wrist,elbow,	3D Accelerometer (ADXL311)
[47]	Belt (left-/right)	3D Accelerometer ADXL202
[5]	Chest	3D Accelerometers (ADXL213, analog)
[4]	Hip, thigh, ankle, arm, wrist	2D Accelerometer (ADXL210E, analog)
[38]	Legs	2D accelerometer (ADXL202JE, analog) and Ball Switches
[66]	Legs (upper), above knee	1D Accelerometer (ADXL05s, analog) , passive infrared sensors, carbon monoxide sensor, microphones, pressure sensors, temperature sensors, touch-sensors and light-sensors
[61]	Near pelvic region	3D Accelerometer (CDXL04M3)
[21]	Pocket	3D Accelerometer (ADXL330, analog)
[36]	Pocket	3D Accelerometer (Cell phone)
[60]	Pocket	2D Accelerometer (ADXL202), GPS
[14]	Shoulder	Sociometer (IR transceiver, a microphone, two accelerometers, on-board storage, and power supply)
[6]	Waist	3D Accelerometer
[71]	Waist	3D Accelerometer and a microphone.
[62]	Waist belt	3D Accelerometer
[26]	Wrist, hip and thigh	2D accelerometer (ADXL202JE), Tilt switches

a very important step; therefore features should be carefully chosen in order to extract relevant information from the input data, because it will have a strong influence in the results of classification. Features selection is an important and essential step in the design of any activity recognition system, in order to design an effective system. The features in different studies were analyzed mainly in time-domain and frequency-domain. In the following we will brief describe features extraction in the time-domain and frequency-domain.

Feature extraction in the Time-Domain

In much of the research, studies were considering only time-domain features due to avoid the complexity of pre-processing that required transformation of the signal into frequencies. They consume little processing power and the algorithms can be applied directly. Table 9.4 shows a summary of papers that consider the time domain features.

Table 9.4: Feature extraction studies in the time domain

Study	Approaches
[37, 4, 70, 32, 61, 75, 20, 27, 49, 44, 22, 24, 11, 69, 63, 64, 41]	Mean
[32, 24, 61, 37, 71, 44, 75, 20, 27, 49, 69, 63, 64, 41]	Variance or standard deviation
[20, 49, 75, 11]	Root mean square (RMS)
[11, 49, 37, 44, 59]	Zero or Mean Crossing Rate
[44, 20, 66, 11]	Derivative
[38, 3, 39, 72, 67]	Peak Count and Amplitude

Feature extraction in the Frequency-Domain

Unlike the time-domain features, the signal should transform data into the frequency domain and this process requires pre-processing and different transformations such as the use of Fast Fourier transform (FFT). Table 9.5 shows the most widely used features in frequency domain.

Table 9.5: Feature extraction studies in the frequency domain

Study	Approaches
[34, 66, 69, 63, 64, 29, 41, 27, 40, 2]	Fast Fourier Transform
[69, 63, 64, 61, 27, 40]	Energy
[69, 63, 64, 41, 23, 27, 40]	Spectral Entropy
[35, 23]	Frequency range power

9.2.3.3 Classification

Next step after the feature extraction is the classification process. In the classification process, the classification algorithm builds up a model (classifiers) for different human activities and then uses these classifier to identify human activities from the test data. A wide range of machine learning approaches and algorithms are used for activity recognition. Most of these approaches have been used for activity recognition which can be categorized into two groups: supervised learning and unsupervised learning.

Supervised learning is a machine learning technique, also sometimes called ”learning with a teacher” in which the system is trained by using a set of training data before it comes into use in classifying the test data. There are two general phases in a supervised learning technique: training and testing. During the training phase the system is taught (trained) by using a set of training data to create a classification model to classify unknown data. During the testing phase, the model of the system is tested using a set of test data to measure the classification accuracy [42]. Training and testing phases are illustrated in Figure 9.2.

The majority of works in activity recognition have been done by using supervised learning methods. A summary of these approaches applied so far is shown in Table 9.6. Supervised learning techniques are mostly used for activity recognition in majority of the researches. Next step is to look at the unsupervised learning techniques which are dissimilar than the supervised learning.

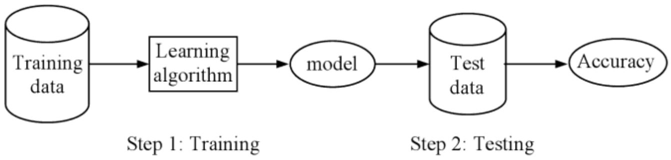


Figure 9.2: The basic of learning process: training and testing [42]

Table 9.6: Supervised learning approaches used for activity recognition

Study	Approaches
[67, 4, 28, 61]	Naive Bayes Classifier
[4, 49, 61]	C4.5 Decision Tree
[35, 26, 66, 61]	Nearest Neighbor
[72, 41, 56]	Hidden Markov Model
[26, 61]	Support Vector Machine
[66]	Kohonen Self-Organising Map

Unsupervised learning by contrast does not use any training or testing data. Instead, it ”tries” to classify the unknown data by separating the data into different classes (clusters). It is a ”learning without teacher” method. The method tries to directly build models not basing itself on any priori-built model or knowledge. It learns from the unlabeled data, the task of this method is to discover classes of similar examples from the unlabeled data and organizes data into similarity groups, which is known as clustering, or by estimating the distribution of data within the input space which is called density estimation [7]. Clustering is the process of organizing unlabeled data into clusters, where the data in the same cluster are similar to each other and the data in different clusters are dissimilar [10]. A summary of the unsupervised learning approaches that are applied for activity recognition is shown in Table 9.7.

Table 9.7: Unupervised learning approaches used for activity recognition

Study	Approaches
[51, 73, 53]	Hidden Markov Model (HMM)
[15]	Hierarchies of HMM
[57]	Hierarchical Dynamic Bayesian Network
[29]	Multiple Eigenspaces
[53]	Gaussian Mixture Models
[46]	Multi-layered FSM

The process flow for unsupervised learning is illustrated in Figure 9.3.

9.2.4 Activity Recognition Performances

Studies have shown different accuracies for activity recognition systems in which the data collection was performed in a controlled laboratory settings (subjects are told how to walk, run etc.), from the experiments in which the data was collected under normal circumstances. As we saw in the data collection section a range of different sensors are used to collect the data. Experiments were performed by placing these sensors in one or multiple locations on the body. A summary of recognition accuracies is shown in the Table 9.8.

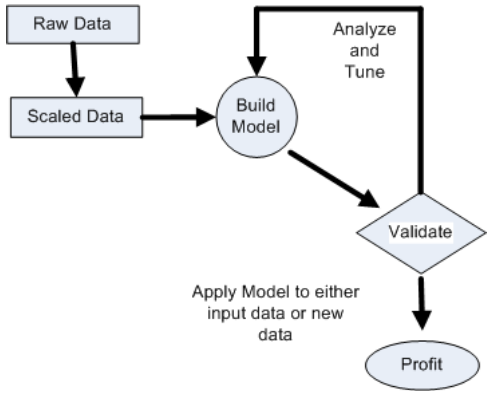


Figure 9.3: Unsupervised Learning Workflow [1]

9.3 Scenario and Proposal

A full automatic wearable sensor (WS) based gait recognition system using mobile devices is proposed in this section. The WS based recognition approach is the newest approach among the gait recognition methods available, i.e Machine Vision (MV) Based and Floor Sensor (FS) Based. WS is based on wearing motion recording sensors on the body of the person in different places; on the waist, pockets, shoes and so forth. Since wearable gait recognition system do not offer a full automatic mechanism today we will in this section give a possible solution to how this system is to be designed and implemented by including activity recognition as a major main step. Sensor based biometric gait research shows an increase in performance over time since 2005 where external dedicated sensors were applied until today where mobile phone accelerometers are being used. And to make gait recognition more stable, some issues need to be taken into consideration which we will see at the following subsections.

9.3.1 Scenario

We will here give some examples on different scenarios where activity recognition and gait recognition would make phones applicable as a security mechanism.

- **Shopping:** When a person is shopping, he or she is performing a lot of walking and standing. Since the user is constantly watching out for new equipments or clothing it will simply mean that the person is performing different activities by walking from one shop to another, from one cashier to another, etc.. In this case we can protect data of the person to ensure security of the phone.
- **Going to Work** People go to work by different means of transport. Some people use car, bicycle or even their motorbike. Since the mobile phone might be lost while walking out of the car or bicycling, it can ensure security. However, if a person is sitting in the car and the phone is standing still, the phone will also recognize that a ”standing still” activity is ongoing, and thus the phone should not be used at all for authentication. In this case, a backup solution should be applied such as using the PIN-code.
- **Fitness/Jogging** Even when people are making fitness, they might loose their phone when running outside their home. Running is still an activity and can also be used as a security mechanism towards authentication to the phone for usage.

These examples are only few out of many. An illustration of which activities can be recognized from gait signal data is shown in Figure 9.4. The interesting point of view here

Table 9.8: Recognition Accuracies.

Study	Recognition Accuracy	Activities Recognized	#TP
[45]	80%	walking, running, cycling, driving, sports	24
[4]	84%	walking, sitting, standing, running, computer work, bicycling, Lying down, etc.	20
[47]	83% - 90%	walking, downstairs, upstairs, opening doors	6
[50]	90%	walking, jogging, upstairs, downstairs, sitting, standing	29
[30]	90.8%	walking (slow, normal, fast), sitting, standing, lying, falling	6
[39]	92.85% - 95.91%	sitting, standing, walking,	8
[32]	65% - 95%	sitting, standing, walking, stairs up/down, whiteboard writing, shake hands, keyboard typing	1
[21]	97,51%	walking, jumping, still, running	11
[22]	99,5%	standing, sitting, lying, walking, running	5

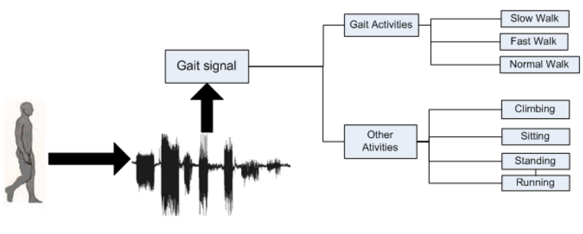


Figure 9.4: Walking and Non-Walking Activities

is that the mobile phone by using activity recognition for identifying activities and gait recognition for identifying the uniqueness of a person, together can establish a security link for mobile phone devices as an access control mechanism. Research has to the best of our knowledge not implemented these two technologies into one full system. What we will see in the next subsection is how we can apply activity and gait recognition approaches together and how this should work like.

9.3.2 Design and Proposal

The detection of everyday routine and leisure activities as we saw earlier like walking, running, sitting, and standing from gait signal recorded from wearable sensors make a step forward in the authentication. There has been done studies on gait recognition for authentication in mobile devices [17], but there are so far no studies in activity recognition for authentication. The data obtained from wearable sensors can be very useful for activity recognition as we have seen in the recent section. Therefore, activity recognition is becoming a necessary step regarding continues authentication that is based on gait using wearable motion recording sensors in mobile devices. A proposal towards full gait recognition includes activity recognition. This simply means that a full automatic system includes:

- **Activity Recognition** Identifying activities from a gait signal where we only focus on stable activities, such as walking normal, slow or fast.

- **Gait Recognition** Extraction of the unique from the stable walking activities to be used for authentication on a mobile device.

Since a full gait signal consist of different activities, we propose to divide the activity recognition in two phases. First phase is segmentation that is to find out where an each activities start and end point is located on the signal as illustrated in Figure 9.5. For this we propose the use of Sliding Windows, Top-Down, Bottom-Up and Sliding Window and Bottom-Up (SWAB) as referred to in section 9.2.3.1. Second phase is the classification where

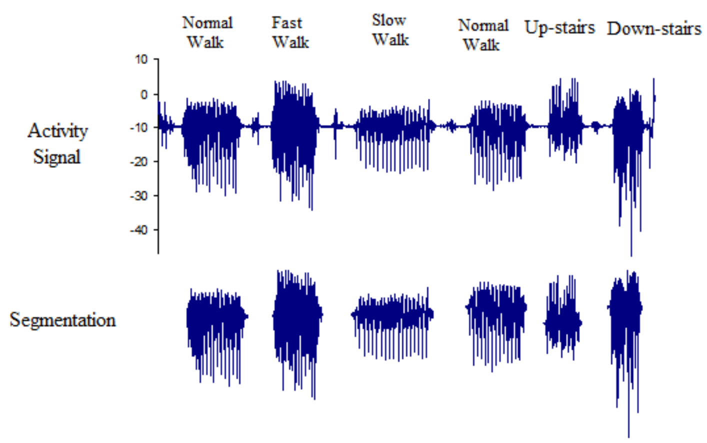


Figure 9.5: A full gait signal without segmentation (upper signal figure) and segmented walks (lower signal figure)

we can see which activities are useful to forward to the gait recognition mechanism as illustrated in Figure 9.6. The classification task as can be seen in Figure 9.6 consists in itself that pre-processing before inputting the data for segmentation, is needed. After the segmentation process we apply feature extraction approaches. Feature extraction is the process of extracting the most relevant information form the data segments. The features extracted then passes through the classification stage. This stage includes the classification process of the data and creation of classifiers which are used to identify different human activities. For the classifications there are different approaches to apply. We thus propose to apply methods that are shown in section 9.2.3.3

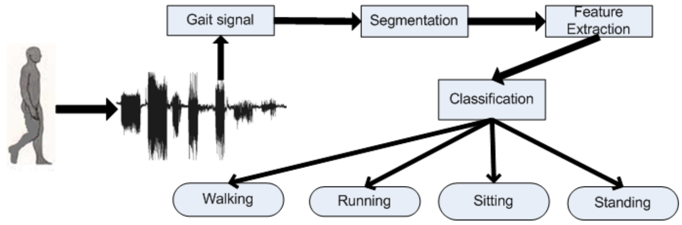


Figure 9.6: Classification of the Activities

9.4 Conclusion

In this paper we have proposed that by using activity recognition and gait recognition we can create a continuous and automatic authentication system on mobile devices. Since wearable sensor based gait recognition do not offer this mechanism today future work will then be to make an implementation of the design which was proposed during this paper. Activity and Gait Recognition has been studied separately in the recent years, but the interest has become so high lately when mobile phones today include these embedded accelerometers. The recognition accuracy for activity recognition has shown great results, which means to be useful for gait an automatic gait recognition system.

9.5 Bibliography

[1] Machine learning - who's the boss? http://awesomeful.net/posts/78-machine-learning-who-s-the-boss. [Online; accessed 13-march-2011]. xi, 136

[2] ALLEN, F. R., AMBIKAIRAJAH, E., LOVELL, N. H., AND CELLER, B. G. An Adapted Gaussian Mixture Model Approach to Accelerometry-Based Movement Classification Using Time-Domain Features. pp. 3600–3603. Available from: `http://dx.doi.org/10.1109/IEMBS.2006.259613`. 134

[3] AMFT, O., STGER, M., AND TRSTER, G. Analysis of chewing sounds for dietary monitoring. In *In UbiComp 2005* (2005), Springer, pp. 56–72. 82, 134

[4] BAO, L., AND INTILLE, S. S. Activity Recognition from User-Annotated Acceleration Data. *Pervasive Computing* (2004), 1–17. Available from: `http://www.springerlink.com/content/9aqflyk4f47khyjd`. 22, 33, 35, 78, 80, 81, 131, 133, 134, 135, 137, 148

[5] BARRALON, P., NOURY, N., AND VUILLERME, N. Classification of daily physical activities from a single kinematic sensor. *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference 3* (2005), 2447–2450. Available from: `http://dx.doi.org/10.1109/IEMBS.2005.1616963`. 36, 133

[6] BIDARGADDI, N., KLINGBEIL, L., AND SARELA, A. Detecting walking activity in cardiac rehabilitation by using accelerometer. *Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on* (2007), 555–560. Available from: `http://dx.doi.org/10.1109/ISSNIP.2007.4496903`. 36, 133

[7] BISHOP, C. M. *Pattern Recognition and Machine Learning*. 2006. 39, 135

[8] BRADY, S., DUNNE, L. E., TYNAN, R., DIAMOND, D., SMYTH, B., AND O'HARE, G. M. P. Garment-based monitoring of respiration rate using a foam pressure sensor. In *Proceedings of the Ninth IEEE International Symposium on Wearable Computers*

(Washington, DC, USA, 2005), IEEE Computer Society, pp. 214–215. Available from: http://portal.acm.org/citation.cfm?id=1104998.1105315. 32, 33, 78, 80, 81, 82, 132

[9] BULLING, A., WARD, J., GELLERSEN, H., AND TROESTER, G. Robust recognition of reading activity in transit using wearable electrooculography. In *Pervasive Computing*, J. Indulska, D. Patterson, T. Rodden, and M. Ott, Eds., vol. 5013 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, 2008, pp. 19–37. 10.1007/978-3-540-79576-6_2. Available from: http://dx.doi.org/10.1007/978-3-540-79576-6_2. 35, 83, 131

[10] CAREY, MICHAEL J., C. S. *Data-Centric Systems and Applications*. 2006. 39, 135

[11] CHAMBERS, G. S., VENKATESH, S., WEST, G. A. W., AND BUI, H. H. Hierarchical recognition of intentional human gestures for sports video annotation. In *16th International Conference on Pattern Recognition* (2002), vol. 2, pp. 1082–1085. Available from: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1048493. 134

[12] CHEN, J., KAM, A. H., ZHANG, J., LIU, N., AND SHUE, L. Bathroom Activity Monitoring Based on Sound. 2005, pp. 47–61. Available from: http://dx.doi.org/10.1007/11428572_4. 18, 132

[13] CHOUDHURY, T., BORRIELLO, G., CONSOLVO, S., HAEHNEL, D., HARRISON, B., HEMINGWAY, B., HIGHTOWER, J., KLASNJA, P., KOSCHER, K., LAMARCA, A., LANDAY, J. A., LEGRAND, L., LESTER, J., RAHIMI, A., REA, A., AND WYATT, D. The Mobile Sensing Platform: An Embedded Activity Recognition System. *IEEE Pervasive Computing 7*, 2 (Apr. 2008), 32–41. Available from: http://dx.doi.org/10.1109/MPRV.2008.39. 31, 35, 80, 131, 148

[14] CHOUDHURY, T., AND PENTLAND, A. Sensing and modeling human networks using the sociometer. In *Proceedings of the 7th IEEE International Symposium on Wearable Computers* (Washington, DC, USA, 2003), ISWC '03, IEEE Computer Society, pp. 216–. Available from: http://portal.acm.org/citation.cfm?id=946249.946901. 133

[15] CLARKSON, B., AND PENTLAND, A. Unsupervised clustering of ambulatory audio and video. In *ICASSP '99: Proceedings of the Acoustics, Speech, and Signal Processing, 1999. on 1999 IEEE International Conference* (Washington, DC, USA, 1999), vol. 6, IEEE Computer Society, pp. 3037–3040. Available from: http://dx.doi.org/10.1109/ICASSP.1999.757481. 40, 135

[16] DERAWI, M. O. Accelerometer-based gait analysis, a survey. In *Norwegian Information Security Conference (NISK)* (Gjøvik, Norway, 2010), NISK '10, Tapir, pp. 33–44. 130

[17] DERAWI, M. O., NICKEL, C., BOURS, P., AND BUSCH, C. Unobtrusive user-authentication on mobile phones using biometric gait recognition. *Intelligent Information Hiding and Multimedia Signal Processing, International Conference on 0* (2010), 306–311. 20, 22, 138

[18] DUNNE, L., WALSH, P., SMYTH, B., AND CAULFIELD, B. Design and evaluation of a wearable optical sensor for monitoring seated spinal posture. *Wearable Computers, IEEE International Symposium 0* (2006), 65–68. 82, 132

[19] ERMES, M., PÄRKKA, J., MANTYJARVI, J., AND KORHONEN, I. Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. *IEEE transactions on information technology in biomedicine : a publication of the IEEE Engineering in Medicine and Biology Society 12*, 1 (Jan. 2008), 20–26. Available from: http://dx.doi.org/10.1109/TITB.2007.899496. 35, 36, 131, 132, 148

[20] GHASEMZADEH, H., LOSEU, V., GUENTERBERG, E., AND JAFARI, R. Sport training using body sensor networks: a statistical approach to measure wrist rotation for golf swing. In *Proceedings of the Fourth International Conference on Body Area Networks* (ICST, Brussels, Belgium, Belgium, 2009), BodyNets '09, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), pp. 2:1–2:8. 134

[21] HE, Z., AND JIN, L. Activity recognition from acceleration data based on discrete consine transform and svm. In *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on* (2009), pp. 5041 –5044. 35, 36, 40, 129, 131, 133, 137, 147, 148

[22] HEE LEE, M., KIM, J., KIM, K., LEE, I., JEE, S. H., AND YOO, S. K. Physical activity recognition using a single tri-axis accelerometer. In *Proceedings of the World Congress on Engineering and Computer Science 2009 Vol I, WCECS '09, October 20 - 22, 2009, San Francisco, USA* (2009), S. I. Ao, C. Douglas, W. S. Grundfest, and J. Burgstone, Eds., Lecture Notes in Engineering and Computer Science, International Association of Engineers, Newswood Limited, pp. 14–17. 35, 40, 131, 134, 137

[23] HEINZ, E. A., KUNZE, K. S., GRUBER, M., BANNACH, D., AND LUKOWICZ, P. Using Wearable Sensors for Real-Time Recognition Tasks in Games of Martial Arts - An Initial Experiment. *Computational Intelligence and Games, 2006 IEEE Symposium on* (2006), 98–102. Available from: `http://dx.doi.org/10.1109/CIG.2006.311687`. 134

[24] HEINZ, E. A., KUNZE, K.-S., SULISTYO, S., JUNKER, H., LUKOWICZ, P., AND TRÖSTER, G. Experimental evaluation of variations in primary features used for accelerometric context recognition. In *in Proceedings of the 1st European Symposium on Ambient Intelligence (EUSAI 2003* (2003), vol. 1, pp. 252–263. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.72.6282`. 134

[25] HUYNH, D. T. G. *Human Activity Recognition with Wearable Sensors*. Ph.D. thesis, TU Darmstadt, Darmstadt, September 2008. Available from: `http://tubiblio.ulb.tu-darmstadt.de/38560/`. ix, xi, 34, 36, 129, 130, 131, 147, 156

[26] HUYNH, T., BLANKE, U., AND SCHIELE, B. Scalable recognition of daily activities with wearable sensors. In *3rd International Workshop on Location- and Context- Awareness (LoCA 2007)* (september 2007), p. 50–67. ix, 20, 21, 22, 23, 24, 25, 26, 27, 32, 33, 77, 78, 80, 81, 82, 133, 135

[27] HUYNH, T., AND SCHIELE, B. Analyzing features for activity recognition. In *sOc-EUSAI '05: Proceedings of the 2005 joint conference on Smart objects and ambient intelligence* (New York, NY, USA, 2005), ACM, pp. 159–163. Available from: `http://dx.doi.org/10.1145/1107548.1107591`. 134

[28] HUYNH, T., AND SCHIELE, B. Towards less supervision in activity recognition from wearable sensors. In *Wearable Computers, 2006 10th IEEE International Symposium on* (2006), pp. 3 –10. 135

[29] HUYNH, T., AND SCHIELE, B. Unsupervised discovery of structure in activity data using multiple eigenspaces. In *2nd International Workshop on Location- and Context-Awareness (LoCA 2006)* (Dublin, Ireland, May 2006). 22, 40, 77, 78, 132, 134, 135

[30] KARANTONIS, D. M., NARAYANAN, M. R., MATHIE, M., LOVELL, N. H., AND CELLER, B. G. Implementation of a Real-Time Human Movement Classifier Using a Triaxial Accelerometer for Ambulatory Monitoring. *Information Technology in Biomedicine, IEEE Transactions on 10*, 1 (2006), 156–167. Available from: `http://dx.doi.org/10.1109/TITB.2005.856864`. 40, 137

[31] Keogh, E. J., Chu, S., Hart, D., and Pazzani, M. J. An online algorithm for segmenting time series. In *Proceedings of the 2001 IEEE International Conference on Data Mining* (Washington, DC, USA, 2001), ICDM '01, IEEE Computer Society, pp. 289–296. Available from: `http://portal.acm.org/citation.cfm?id=645496.657889`. 36, 132

[32] Kern, N., Schiele, B., and Schmidt, A. Multi-Sensor Activity Context Detection for Wearable Computing. In *In Proc. EUSAI, LNCS* (2003), vol. 2875, pp. 220–232. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.6.3308`. 18, 133, 134, 137

[33] Khan, A. M., Lee, Y. K., Lee, S. Y., and Kim, T. S. Human Activity Recognition via an Accelerometer-Enabled-Smartphone Using Kernel Discriminant Analysis. pp. 1–6. Available from: `http://dx.doi.org/10.1109/FUTURETECH.2010.5482729`. 35, 131

[34] Krause, A., München, T. U., and Smailagic, A. Unsupervised, dynamic identification of physiological and activity context in wearable computing. In *In Proceedings of the 7th International Symposium on Wearable Computers* (2003), pp. 88–97. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.135.5809`. 22, 78, 132, 134

[35] Kunze, K., Barry, M., Heinz, E. A., Lukowicz, P., Majoe, D., and Gutknecht, J. Towards recognizing tai chi an initial experiment using wearable sensors. In *Heinz1, Paul Lukowicz, Dennis Majoe, Jurg Gutknecht; Institute for Computer Systems and Networks UMIT* (2006). 132, 134, 135

[36] Kwapisz, J. R., Weiss, G. M., and Moore, S. A. Activity recognition using cell phone accelerometers. *Human Factors* (2010), 1018. Available from: `http://storm.cis.fordham.edu/~gweiss/papers/sensorKDD-2010.pdf`. 35, 36, 131, 133, 148

[37] Laerhoven, K. V., and Cakmakci, O. What shall we teach our pants? In *Proceedings of the 4th IEEE International Symposium on Wearable Computers* (Washington, DC, USA, 2000), ISWC '00, IEEE Computer Society, pp. 77–. Available from: `http://portal.acm.org/citation.cfm?id=851037.856531`. 37, 134

[38] Laerhoven, K. V., and Gellersen, H.-W. Spine versus porcupine: A study in distributed wearable activity recognition. In *Proceedings of the Eighth International Symposium on Wearable Computers* (Washington, DC, USA, 2004), ISWC '04, IEEE Computer Society, pp. 142–149. Available from: `http://dx.doi.org/10.1109/ISWC.2004.40`. 22, 29, 32, 33, 78, 80, 81, 82, 132, 133, 134

[39] Lee, S. W., and Mase, K. Activity and Location Recognition Using Wearable Sensors. *IEEE Pervasive Computing 1*, 3 (July 2002), 24–32. Available from: `http://dx.doi.org/10.1109/MPRV.2002.1037719`. 83, 134, 137

[40] Lester, J., Choudhury, T., and Borriello, G. A Practical Approach to Recognizing Physical Activities. In *Pervasive Computing*, K. Fishkin, B. Schiele, P. Nixon, and A. Quigley, Eds., vol. 3968 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, Berlin, Heidelberg, 2006, ch. 1, pp. 1–16. Available from: `http://dx.doi.org/10.1007/11748625_1`. 35, 131, 134, 148

[41] Lester, J., Choudhury, T., Kern, N., Borriello, G., and Hannaford, B. A hybrid discriminative/generative approach for modeling human activities. In *In Proc. of the International Joint Conference on Artificial Intelligence (IJCAI)* (2005), pp. 766–772. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.77.5776`. 131, 134, 135

[42] Liu, B. *Web Data Mining: Exploring Hyperlinks, Contents, and Usage Data (Data-Centric Systems and Applications)*, 1st ed. 2007. corr. 2nd printing ed. Springer, Jan. 2009. Available from: `http://www.amazon.com/exec/obidos/redirect?tag=citeulike07-20&path=ASIN/3540378812`. ix, xi, 39, 134, 135

[43] Logan, B., Healey, J., Philipose, M., Tapia, E., and Intille, S. A Long-Term Evaluation of Sensing Modalities for Activity Recognition. In *UbiComp 2007: Ubiquitous Computing*, J. Krumm, G. D. Abowd, A. Seneviratne, and T. Strang, Eds., vol. 4717 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg, Berlin, Heidelberg, 2007, ch. 28, pp. 483–500. Available from: `http://dx.doi.org/10.1007/978-3-540-74853-3_28`. 82, 132

[44] Lombriser, C., Bharatula, N. B., Roggen, D., and Tröster, G. On-body activity recognition in a dynamic sensor network. In *Proceedings of the ICST 2nd international conference on Body area networks* (ICST, Brussels, Belgium, Belgium, 2007), BodyNets '07, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), pp. 17:1–17:6. Available from: `http://portal.acm.org/citation.cfm?id=1460232.1460249`. ix, 37, 38, 134

[45] Long, X., Yin, B., and Aarts, R. Single-accelerometer-based daily physical activity classification. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE* (2009), pp. 6107 –6110. 35, 40, 131, 137, 148

[46] Mahajan, D., Kwatra, N., Jain, S., Kalra, P., and Banerjee, S. A framework for Activity Recognition and Detection of Unusual Activities. In *Proc. Indian Conference on Computer Vision, Graphics and Image Processing* (December 2004). 40, 135

[47] Mäntyjärvi, J., Himberg, J., and Seppänen, T. Recognizing human motion with multiple acceleration sensors. vol. 2. Available from: `http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=973004`. 82, 133, 137

[48] Mathie, M., Lovell, N., Coster, A., and Celler, B. Determining activity using a triaxial accelerometer. In *Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, 2002. Proceedings of the Second Joint* (2002), vol. 3, pp. 2481 – 2482 vol.3. 35, 131, 148

[49] Maurer, U., Smailagic, A., Siewiorek, D. P., and Deisher, M. Activity recognition and monitoring using multiple sensors on different body positions. In *Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks* (Washington, DC, USA, 2006), IEEE Computer Society, pp. 113–116. Available from: `http://portal.acm.org/citation.cfm?id=1121990.1122269`. 18, 35, 131, 132, 134, 135

[50] Maurer, U., Smailagic, A., Siewiorek, D. P., and Deisher, M. Activity recognition and monitoring using multiple sensors on different body positions. In *Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks* (Washington, DC, USA, 2006), IEEE Computer Society, pp. 113–116. Available from: `http://portal.acm.org/citation.cfm?id=1121990.1122269`. 40, 137

[51] Minnen, D., Starner, T., Essa, M., and Isbell, C. Discovering Characteristic Actions from On-Body Sensor Data. *Wearable Computers, 2006 10th IEEE International Symposium on* (2006), 11–18. Available from: `http://dx.doi.org/10.1109/ISWC.2006.286337`. 40, 135

[52] Naeem, U., Bigham, J., and Wang, J. Recognising activities of daily life using hierarchical plans. In *Proceedings of the 2nd European conference on Smart sensing and context*

(Berlin, Heidelberg, 2007), EuroSSC'07, Springer-Verlag, pp. 175–189. Available from: http://portal.acm.org/citation.cfm?id=1775377.1775391. 83, 132

[53] Nguyen, A., Moore, D., and McCowan, I. Unsupervised clustering of free-living human activities using ambulatory accelerometry. *Conf Proc IEEE Eng Med Biol Soc 2007* (2007), 4895–8. Available from: http://www.biomedsearch.com/nih/Unsupervised-clustering-free-living-human/18003103.html. 40, 135

[54] Nowozin, S., Bakir, G., and Tsuda, K. Discriminative subsequence mining for action classification. In *Computer Vision, 2007. ICCV 2007. IEEE 11th International Conference on* (2007), pp. 1 –8. 31, 33, 82, 132

[55] Oliver, N., and Flores-Mangas, F. Healthgear: A real-time wearable system for monitoring and analyzing physiological signals. *Wearable and Implantable Body Sensor Networks, International Workshop on 0* (2006), 61–64. 82, 132

[56] Patterson, D., Fox, D., Kautz, H., and Philipose, M. Fine-grained activity recognition by aggregating abstract object usage. In *Wearable Computers, 2005. Proceedings. Ninth IEEE International Symposium on* (2005), pp. 44 – 51. 82, 132, 135

[57] Patterson, D. J., Liao, L., Gajos, K., Collier, M., Livic, N., Olson, K., Wang, S., Fox, D., and Kautz, H. Opportunity Knocks: A System to Provide Cognitive Assistance with Transportation Services. 2004, pp. 433–450. Available from: http://www.springerlink.com/content/xh22c1262bny1fly. 40, 135

[58] Philipose, M., Fishkin, K., Perkowitz, M., Patterson, D., Fox, D., Kautz, H., and Hahnel, D. Inferring activities from interactions with objects. *Pervasive Computing, IEEE 3*, 4 (2004), 50 – 57. 82, 132

[59] Pirttikangas, S., Fujinami, K., and Nakajima, T. Feature selection and activity recognition from wearable sensors. In *UCS* (2006), pp. 516–527. Available from: http://www.springerlink.com/content/gw3x126p42786532. 36, 132, 134

[60] Randell, C., and Muller, H. Context awareness by analysing accelerometer data. In *Digest of Papers. Fourth International Symposium on Wearable Computers* (Los Alamitos, CA, USA, 2000), vol. 0, IEEE Comput. Soc, pp. 175–176. Available from: http://dx.doi.org/10.1109/ISWC.2000.888488. 36, 133

[61] Ravi, N., Dandekar, N., Mysore, P., and Littman, M. L. Activity Recognition from Accelerometer Data. *American Association for Artificial Intelligence* (2005). Available from: http://paul.rutgers.edu/~{}nravi/accelerometer.pdf. 82, 133, 134, 135

[62] Sekine, M., Tamura, T., Akay, M., Togawa, T., and Fukui, Y. Analysis of acceleration signals using wavelet transform. *Methods Inf Med 39*, 2 (2000), 183–5. Available from: http://www.biomedsearch.com/nih/Analysis-acceleration-signals-using-wavelet/10892260.html. 36, 133

[63] Stikic, M., Huynh, T., Van Laerhoven, K., and Schiele, B. ADL Recognition Based on the Combination of RFID and Accelerometer Sensing. In *Proceedings of the 2nd International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health 2008)* (Tampere, Finland, January 2008), IEEE Xplore, IEEE Xplore, p. 258–263. 132, 134

[64] Stikic, M., Van Laerhoven, K., and Schiele, B. Exploring semi-supervised and active learning for activity recognition. In *Proceedings of the 12th International Symposium on Wearable Computers (ISWC 2008)* (Pittsburgh, USA, September 2008), IEEE Press, IEEE Press, pp. 81–90. 83, 134

[65] TAPIA, E. M., INTILLE, S. S., AND LARSON, K. Activity Recognition in the Home Using Simple and Ubiquitous Sensors. In *Pervasive Computing*, A. Ferscha and F. Mattern, Eds., vol. 3001 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, 2004, pp. 158–175–175. Available from: `http://dx.doi.org/10.1007/978-3-540-24646-6_10`. 82, 132

[66] VAN LAERHOVEN, K., AND CAKMAKCI, O. What shall we teach our pants? In *Wearable Computers, 2000. The Fourth International Symposium on* (2000). 22, 30, 77, 78, 80, 132, 133, 134, 135

[67] VAN LAERHOVEN, K., KERN, N., GELLERSEN, H.-W., AND SCHIELE, B. Towards a wearable inertial sensor network. In *In Proceedings of IEE Eurowearable* (2003), pp. 125–130. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.65.6072`. 18, 134, 135

[68] WANG, N., AMBIKAIRAJAH, E., LOVELL, N. H., AND CELLER, B. G. Accelerometry based classification of walking patterns using time-frequency analysis. *Conf Proc IEEE Eng Med Biol Soc 2007* (2007), 4899–902. Available from: `http://www.biomedsearch.com/nih/Accelerometry-based-classification-walking-patterns/18003104.html`. 35, 131, 148

[69] WANG, S., PENTNEY, W., POPESCU, A.-M., CHOUDHURY, T., AND PHILIPOSE, M. Common Sense Based Joint Training of Human Activity Recognizers. In *In: Proceedings of the 20th International Joint Conference on Artificial Intelligence* (2007), pp. 2237–2242. Available from: `http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.61.5347`. 82, 132, 134

[70] WANG, S., YANG, J., CHEN, N., CHEN, X., AND ZHANG, Q. Human Activity Recognition with User-Free Accelerometers in the Sensor Networks. vol. 2, pp. 1212–1217. Available from: `http://dx.doi.org/10.1109/ICNNB.2005.1614831`. 134

[71] WARD, J. A., LUKOWICZ, P., AND TRÖSTER, G. Gesture spotting using wrist worn microphone and 3-axis accelerometer. In *sOc-EUSAI '05: Proceedings of the 2005 joint conference on Smart objects and ambient intelligence* (New York, NY, USA, 2005), ACM Press, pp. 99–104. Available from: `http://dx.doi.org/10.1145/1107548.1107578`. 36, 133, 134

[72] WARD, J. A., LUKOWICZ, P., TROSTER, G., AND STARNER, T. E. Activity recognition of assembly tasks using body-worn microphones and accelerometers. *IEEE Trans. Pattern Anal. Mach. Intell. 28* (October 2006), 1553–1567. Available from: `http://dx.doi.org/10.1109/TPAMI.2006.197`. 22, 33, 78, 134, 135

[73] WYATT, D., PHILIPOSE, M., AND CHOUDHURY, T. Unsupervised activity recognition using automatically mined common sense. In *Proceedings of the 20th national conference on Artificial intelligence - Volume 1* (2005), AAAI Press, pp. 21–27. Available from: `http://portal.acm.org/citation.cfm?id=1619338`. 135

[74] YANG, J., WANG, S., CHEN, N., CHEN, X., AND SHI, P. Wearable accelerometer based extendable activity recognition system. In *Robotics and Automation (ICRA), 2010 IEEE International Conference on* (May 2010), pp. 3641 –3647. 35, 131

[75] YANG, J.-Y., WANG, J.-S., AND CHEN, Y.-P. Using acceleration measurements for activity recognition: An effective learning algorithm for constructing neural classifiers. *Pattern Recogn. Lett. 29* (December 2008), 2213–2220. Available from: `http://dx.doi.org/10.1016/j.patrec.2008.08.002`. 134

[76] ZHU, C., AND SHENG, W. Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on* (2011). 36, 132

Chapter 10

Activity Recognition Using Smart Phones

Abstract

In this paper we analyze activity recognition to ensuring that only the authorized user can access the data in a mobile phone. Since recent gait recognition research only focus on manual extraction of walking activities from the accelerometer signal, we analyze the importance and performance of activity recognition that would reduce the disadvantages of gait recognition by identifying the activities of a person continuously and automatically. Activity recognition would not only make it possible to authenticate the user in different daily activities like slow walking, normal walking, fast walking even running, but also help in avoiding authentication when the user is in passive state like sitting, standing still, etc. This is one of the key factors and an interesting challenge which would benefit the data security area.

10.1 Introduction

In recent years, activity recognition has become a very important field of research due to its application in many different areas such as health care, fitness, industrial application, security, entertainment, etc.. The goal of activity recognition is to recognize and track human activities, which is also an important goal of ubiquities computing [4]. Computers are becoming more pervasive in modern society by integrating in our phones, music players, cars etc. The idea of ubiquitous computing is to integrate computers into our environment, everyday objects and activities etc, to become assistance in our everyday lives and work [5].

Today, whenever we use computer systems, they demand authentication as a measure of security. Typically, we perform the authentication at login time with either a password, token, biometric characteristic and/or a combination of these. Performing the last mentioned measure is a stronger guarantee that the claimed user logging in is not a impostor but an authorized user. An issue raises that, not many systems of security requires any further measure once the user is granted access thus assuming that the user is continuously legitimated into the system. Continuous authentication insurance of the user's legitimacy is of high importance in critical or high security environments, this means that it is necessary to continuously ensure that the user is the legitimated one. Therefore, performing the user authentication continuously while the system is actively used is something essential. Nevertheless, this kind of authentication needs to be "attractive" for the user. A very good solution for continues authentication is activity recognition from the gait signal.

Last generation of mobile devices (smart phones, PDA etc) are more sophisticated and they come with built-in sensors like accelerometers, gyro-scopes, Global Positioning Systems (GPS), etc., for example accelerometers can record the motion of the body and provide sufficient data that can be used for recognizing activities. Thus, accelerometers are becoming a very important tool due to good results in activity recognition: they are cheap, small, effective, require little energy, they are not sensitive on the conditions of the environment etc.. Because of these advantages of accelerometers they are incorporated in newer mobile devices, e.g. the iPhones, iPod, iPad, HTC etc.

The majority of studies for activity recognition are performed by using wearable sensors. Several studies have shown that wearable sensors are adequate for activity recognition. The identification of everyday routine and leisure activities such as walking, running, biking, sitting, climbing, lying, etc. have been analyzed in by several researchers [10, 6, 9, 8, 1, 2, 3, 7, 4] . In all these studies different sensors were used such as accelerometers which were embedded in wearable sensing devices to collect the needed data. The types of sensors used for activity recognition will be discussed in the next section. Accelerometer sensors are very useful for low-powered equipments like smart phones, tablet computers with applications that are suitable for real-time detection of user's activities. Physical activities such as walking, walking up/down stairs standing, sitting, and running have been studied by some of the researchers using different accelerometers sensors.

10.2 Experiment

In order to acquire acceleration data we used a Mobile Phone called Motorola Milestone. It consists of a triaxial accelerometer which can measure body motion. The acceleration range of the accelerometer is between -2g and +2g with a frequency sampling about 100 samples per second. In the experiment we asked volunteers to perform different activities, namely walking normal, fast and slow. The test-subjects attached the mobile phone to a belt and was placed on the right leg. The volunteers was asked to perform the three mentioned types of activities 15 times for the same fixed distance of around 29 meters for one activity, that would give 29 * 15 = 435 meters of walking for one user per session. The session includes random chosen activities (normal, fast or slow) equally distributed. The volunteers in the experiment were students and employees from all places. In total, 45 subjects (15 females and 30 males) participated where most of them used shoes with flat sole. The age range was from 9 to 59 years old.

10.3 Feature Extraction and Analysis

Since a full gait signal consist of different walking and non-walking activities, we must apply a main analysis approach before we are able to extract features for activity and gait recognition. This approach is for common usage and known as segmentation, that is to find out where walking and non-walking activity are located.

10.3.1 Segmenation

A visual description of the segmentation approach is illustrated in Figure 10.1. The data used are the resultant vector of all three (x,y,z) accelerations. The figure is just an excerpt of the data that is used for each subject. For the analysis data we have the gait signal consist of 15 activities that needs to be segmented first. The experiment was set up in such a way that the relevant tasks were separated from each other by periods of inactivity, i.e. standing still, turning around and standing still again. In Figure 10.1 you can see this period of inactivity clearly between two activities as a more or less "flat line" with a small burst of activity in the middle due to the turning around.

The first step of the data segmentation for this data set has been performed by looking at activity over a short time interval. In particular for each datapoint we looked at the interval starting 25 samples before that data point to 25 samples after that data point (i.e. an interval of 51 samples representing 0.51 seconds of collected data). If the maximal difference in acceleration values collected in that interval was above a threshold, then we concluded that an activity was going on for that datapoint. This procedure was repeated for all datapoints that had at least 25 datapoints before and after it.

In the second step we looked at the intervals where we detected activity and inactivity and removed all intervals that were too short. For example if we find an interval of activity

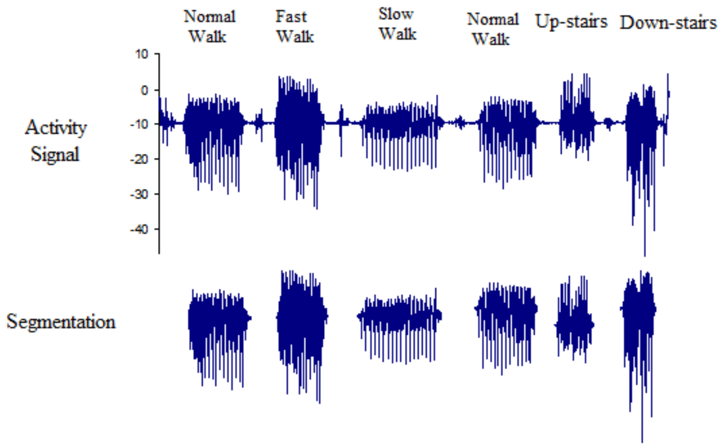


Figure 10.1: A full gait signal without segmentation (upper signal figure) and segmented walks (lower signal figure)

of length 1100, followed by an interval of inactivity of length 10 and then followed by an interval of activity of length 490, then we concluded that the interval of inactivity of length 10 was misclassified and the three intervals were combine to an interval of length $1600 = 1100 + 10 + 490$ of activity. In the same manner short intervals of activity between longer intervals of inactivity were removed. By removing these short intervals in increasing length we were able to also remove the short bursts of activity from the turning around in the middle of the ”flat line” between the activities from the experiment.

10.3.2 Gait Cycle Extraction

The raw segmented data retrieved needs now to be processed in order to create robust templates for each subject. From this raw data the repeating cycles are extracted for each person. A brief description of the steps conducted for feature extraction is given in the following:

Time Interpolation: Due to the android SDK, the phone only outputs data values whenever there is a change in the sensor. Therefore, the time intervals between two sample points (acceleration values) are not always equal, which requires time interpolation. This ensures that the time-interval between two sample-points will be fixed.

Filtering: Removal of noise is done by applying a weighted moving average (WMA) filter.

Cycle length estimation: From the data it is known that the cycle length is between $80-120$ samples. To compute the average cycle length a small subset from the center of the data is extracted and compared with other subsets of similar length. Based on the distance scores between these subsets, the average cycle length is computed.

Cycle Detection: The cycle detection starts from a minimum point $P_{start} = P_{min}$ around the center of the walk. From this point, cycles are detected in both directions. By adding the average length to P_{start}, the estimated ending point $P_{end} = P_{start} + averageLength$ is retrieved (in opposite direction: $P_{end} = P_{start} - averageLength$). The cycle end is defined to be the minimum in the interval of +/- 10% (of the average cycle length) from the estimated end point, see figure 10.2. This process will be repeated from the new end point until all cycles are detected. Finally after going through previous phases and finding the minimum points we are ready to start with the actual detection and able to find the beginning and end of each cycle. This is done by first searching cycles forward from the starting location point detected in the previous phase, and when forward searching is complete we

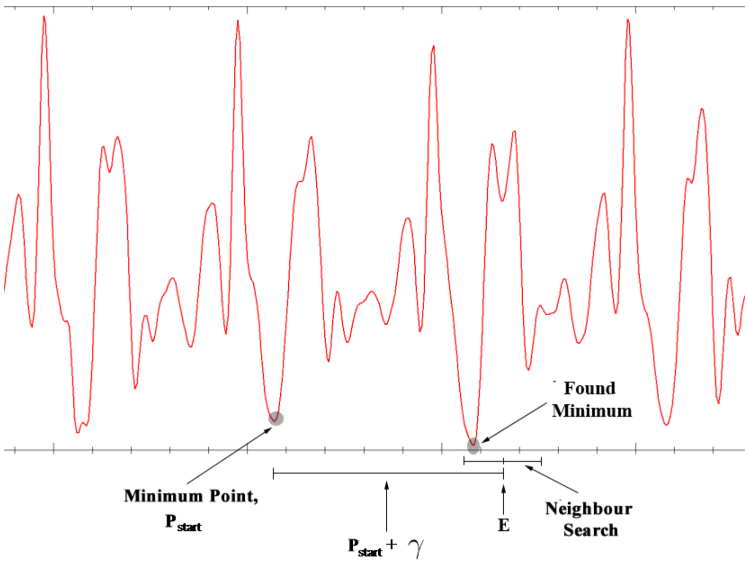


Figure 10.2: Cycle Detection

repeat this process by searching backwards. The cycles extracted are would then be stored as shown in Figure 10.3.

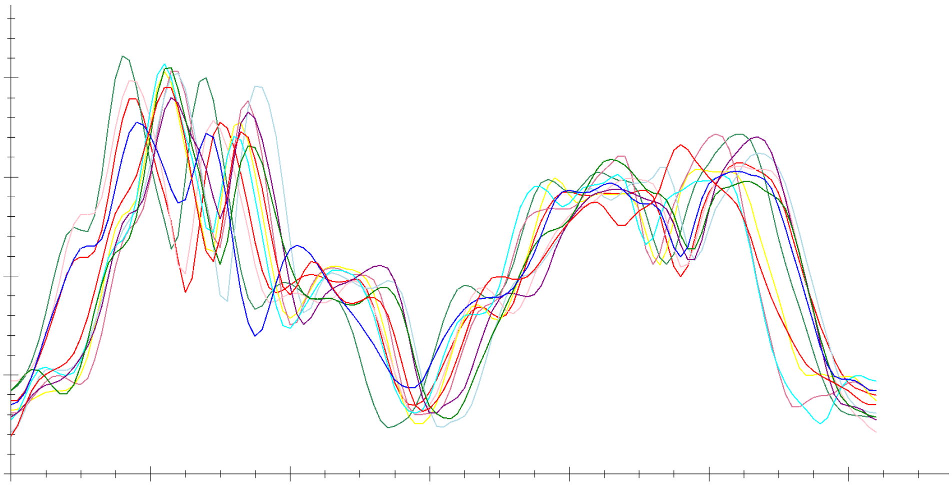


Figure 10.3: The cycles extracted from normal walk

10.3.3 Activity Recognition Analysis

Activity recognition consist of two phases. First phase is the extraction of features from gait cycles extracted for each walk that was segmented. In the second phase we apply different classification approaches to evaluate the accuracy from the extracted features. Both phases are described in more details below.

10.3.3.1 Features

We need to select and calculate individual features for each activity performed. Feature extraction for activity recognition is very important step. They need to be carefully chosen

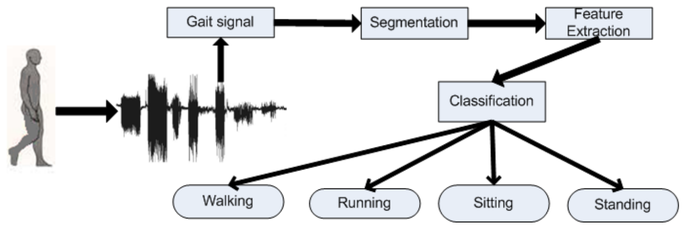


Figure 10.4: Classification of the Activities

due to strong influence in the result of final classification. For each of the 15 walks per user we have selected four features to extract for each cycles: Standard Deviation, Minimum valuse, Maximum Value, and Cyclelenght. The reason why we chose these feature is because each of them output different values for different activities.

10.3.3.2 Classification

The classification task as can be seen in Figure 10.4 consists in itself that preprocessing before inputting the data for segmentation, is needed. After the segmentation process we apply feature extraction approaches. Feature extraction is the process of extracting the most relevant information form the data segments. The features extracted then passes through the classification stage. This stage includes the classification process of the data and creation of classifiers which are used to identify different human activities. For the classifications there are different approaches to apply. The evaluation has been calculated by using the open source software called WeKa. Weka is a collection of machine learning algorithms, and it contains tools for data pre-processing, classification, regression, clustering, association rules etc.

10.4 Results

Before introducing the results separately for both activity and gait recognition, we will first propose a novel system to be developed in order to understand why gait recognition system is strongly depended on activity identification for security reasons. Figure 10.5 illustrates a scenario on how the system should be used. Following the black arrow, we first perform the so-called template creation for different kind of activities. This is done in way that the subject is training the system, and thus, the different template creation for different activites, i.e., fast, normal, and slow walk templates are stored into a database in a mobile devices. Next time the subject is going to walk with his mobile phone and is going to get authenticated (red arrow), the mobile devices initially extracts information about which activity has been performed. If the walk extracted was a normal walk, then we compare the normal walk probe template against the normal walk reference template in the database. In this case, we discard to compare the probe reference template with other than different types of walking templates. Thus, we ensure that the probability of false matches are lower than comparing the probe template against all templates in the database.[1]

10.4.1 Activity Recognition

With the extracted features from fifteen session where each session consist of one of the three different walking activities (normal, fast and slow) performed by 45 subjects we did

[1]When a user performs any activity the system first checks if it is cyclic, i.e. if cycles can be detected. If not, then the data is ignored. If a cyclic activity is detected, then the system will try to match it against one of the three known activities, meaning that any untrained (cyclic) activity will be matched incorrectly to one of the trained activities.

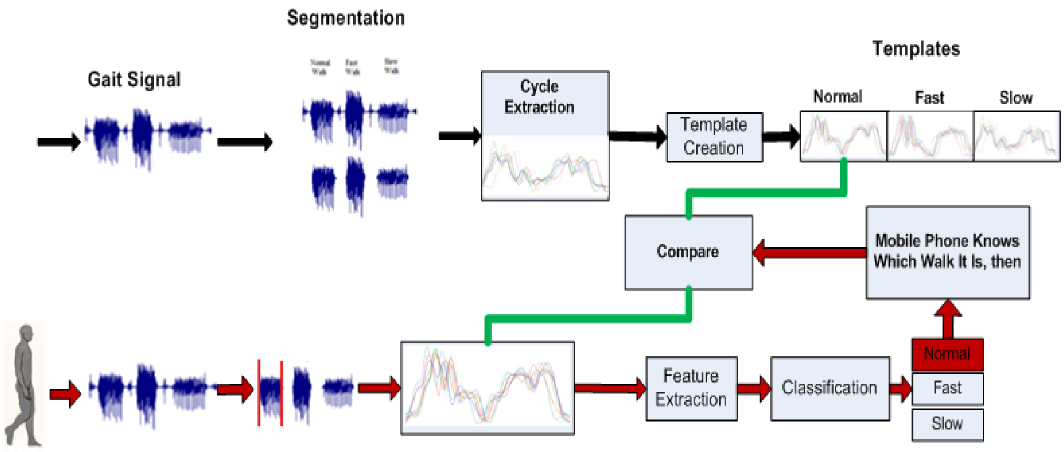


Figure 10.5: Authentication Process System. Black arrow indicates the process towards template protection. Red arrow indicates activity classification and green arrow the comparison

two different evaluations; personal based and global based. We applied supervised learning approaches consisted of both training and testing data and several known algorithms. Therefore, we have split the data into training and testing set by using cross validation. Cross-validation with k-fold uses k-1 folds for training and the remaining one for training, and splits the data by choosing randomly, where k = 10.

Personal Cross Validation: The first performance evaluation we did was cross validation for individual-based activity recognition. This means that we look separately at each users's activity performance. Table 10.1 shows the results of classification for different classifiers used. From the results we see the great performance of distinguishing one activity from another. The best retrieved result was given by LMT (Logistic Model Trees) with an accuracy of 96.08%, also an accuracy of 94.88% was achieved by BayesNet. Accuracy rate of 96.08% and 94.88% indicate how useful are these two algorithms for correctly identifying different activities performed by a subject.

Table 10.1: Crossvalidation

Classifier	Personal	Global
BayesNet	94.88%	73.62%
NaiveBayes	89.31%	71.57%
LibSVM	92.59%	79.58%
MultilayerPercepton	92.77%	73.13
RBFNetwork	91.98%	72.87
RandomTree	93.87%	75.16
LMT	96.08%	79.62

Global Cross Validation: Second test was global cross validation. In this test we merged all data together from all sessions of all 45 subjects into one file. In contrast to the personal cross validation, these results shows how similar or different each subjects fast,slow, and normal walk is from each other for all users. From a performance point of view, we would like to strive after higher accuracies. The results shows that the LMT and LibSVM performs better with an average recognition rate of 79.62% and 79.58%, for four features. This clearly shows that the recognition accuracy is lower compared to cross validation used for individual-based activities classification. This is due to the fact that some peoples normal walk might look like other peoples slow or fast walk, vice versa. These results are satisfactory since peoples walking types and speed are very dissimilar so that we would have overlaps.

10.5 Conclusion

This paper looks at interesting aspects of the biometric feature gait and its application to be developed by using activity recognition. A novel, simple and rich authentication system has been analyzed and proposed. The proposed system in using activity recognition for gait recognition is applied to data from 45 volunteers. Activity recognition is a new area of study and in the last decade is becoming an interesting research field duo to its application in many areas. In our experiment we included stable walking activities like normal, fast and slow. Future work would be to include more circumstances like, walking upstairs and downstairs, walking up- or downhill. Another interesting research topic would be looking at different environments and performing an experiment under normal circumstances and not only controlled laboratory settings where subject are told how to walk. And finally also look at the approaches for segmentation and classification.

10.6 Bibliography

[1] BAO, L., AND INTILLE, S. S. Activity Recognition from User-Annotated Acceleration Data. *Pervasive Computing* (2004), 1–17. Available from: `http://www.springerlink.com/content/9aqflyk4f47khyjd`. 22, 33, 35, 78, 80, 81, 131, 133, 134, 135, 137, 148

[2] CHOUDHURY, T., BORRIELLO, G., CONSOLVO, S., HAEHNEL, D., HARRISON, B., HEMINGWAY, B., HIGHTOWER, J., KLASNJA, P., KOSCHER, K., LAMARCA, A., LANDAY, J. A., LEGRAND, L., LESTER, J., RAHIMI, A., REA, A., AND WYATT, D. The Mobile Sensing Platform: An Embedded Activity Recognition System. *IEEE Pervasive Computing 7*, 2 (Apr. 2008), 32–41. Available from: `http://dx.doi.org/10.1109/MPRV.2008.39`. 31, 35, 80, 131, 148

[3] ERMES, M., PÄRKKA, J., MANTYJARVI, J., AND KORHONEN, I. Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions. *IEEE transactions on information technology in biomedicine : a publication of the IEEE Engineering in Medicine and Biology Society 12*, 1 (Jan. 2008), 20–26. Available from: `http://dx.doi.org/10.1109/TITB.2007.899496`. 35, 36, 131, 132, 148

[4] HE, Z., AND JIN, L. Activity recognition from acceleration data based on discrete consine transform and svm. In *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on* (2009), pp. 5041 –5044. 35, 36, 40, 129, 131, 133, 137, 147, 148

[5] HUYNH, D. T. G. *Human Activity Recognition with Wearable Sensors*. Ph.D. thesis, TU Darmstadt, Darmstadt, September 2008. Available from: `http://tubiblio.ulb.tu-darmstadt.de/38560/`. ix, xi, 34, 36, 129, 130, 131, 147, 156

[6] KWAPISZ, J. R., WEISS, G. M., AND MOORE, S. A. Activity recognition using cell phone accelerometers. *Human Factors* (2010), 1018. Available from: `http://storm.cis.fordham.edu/~gweiss/papers/sensorKDD-2010.pdf`. 35, 36, 131, 133, 148

[7] LESTER, J., CHOUDHURY, T., AND BORRIELLO, G. A Practical Approach to Recognizing Physical Activities. In *Pervasive Computing*, K. Fishkin, B. Schiele, P. Nixon, and A. Quigley, Eds., vol. 3968 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, Berlin, Heidelberg, 2006, ch. 1, pp. 1–16. Available from: `http://dx.doi.org/10.1007/11748625_1`. 35, 131, 134, 148

[8] LONG, X., YIN, B., AND AARTS, R. Single-accelerometer-based daily physical activity classification. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE* (2009), pp. 6107 –6110. 35, 40, 131, 137, 148

[9] MATHIE, M., LOVELL, N., COSTER, A., AND CELLER, B. Determining activity using a triaxial accelerometer. In *Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, 2002. Proceedings of the Second Joint* (2002), vol. 3, pp. 2481 – 2482 vol.3. 35, 131, 148

[10] WANG, N., AMBIKAIRAJAH, E., LOVELL, N. H., AND CELLER, B. G. 35, 131, 148

Chapter 11

Gait and Activity Recognition using Commercial Phones

Abstract

In this paper we develop an application framework for gait and activity recognition in a commercial mobile phone. The activity recognition feature allows individuals to enroll various activities, such as running, walking, or standing, into the phone, and the system can then identify when those activities are performed. The gait recognition feature learns particular characteristics of how participants walk, allowing the phone to identify its user. The gait recognition is further dependent on the activity recognition, since the mobile phone should identify activities before verifying the user with gait recognition.

11.1 Introduction

The combination between gait and activity recognition as a biometric is a relatively new area of study, within the realms of mobile phones. It has been receiving growing interest within the mobile phone community and a number of gait approaches have been developed. Initial studies into gait suggested that gait was a "unique" personal characteristic, with cadence and was cyclic in nature in 1967 [14]. Later, Johansson [10] attached moving lights onto human subjects on all the major body parts and showed these moving patterns to human observers. The observers could recognize the biological patterns of gait from the moving light displays (MLDs), even when some of the markers were detached, once again indicating gait as a potential candidate as a prominent biometric.

Research on accelerometer-based gait recognition started in 2005 by Ailisto et al. [1] and was further investigated by Gafurov [7]. In the initial stages, dedicated accelerometers were used and worn to different body parts like the feet, hip, arm or ankle. Only recently researchers started to use smart phones as "sensors" [5], [6], [11]. Research can be divided in two main groups. Either so-called gait cycles are extracted from the sensor data or the data are divided into segments from which features are extracted. Gait cycles correspond to two steps and can be compared using distances like Dynamic Time Warping (DTW) [17] or Cyclic Rotation Metric (CRM) [4]. For comparison of feature vectors the prominent approach is to use machine learning algorithms that are well established in other pattern recognition domains such as speaker recognition. These promising approaches include neural networks [11], Hidden Markov Models [16] and Support Vector Machines [15].

Gait recognition can be seen as advantageous over other forms of biometric identification techniques for the the following two reasons *1) Unobtrusive* meaning that the gait of a person walking, can be extracted without the user knowing they are being analyzed and without any cooperation from the user in the information gathering stage unlike fingerprinting or retina scans *2) Difficult to mimic* meaning that the gait of an individual is difficult to mimic, by trying to do so the mimicker will appear more unnatural and in the same time not able to exactly the same walk. With other biometrics techniques such as fingerprint recognition, the individuals fingerprint can easily be faked.

However, an individuals gait can even be affected by certain challenges such as *1) Stimulants* meaning that drugs and alcohol may affect the way in which a person gaits *2) Physical* which changes a person during pregnancy, after an accident/disease affecting the leg, or after severe weight gain/loss may affect the movement characteristic of an individual *3) Psychological* where a persons mood may affect an individuals gait characteristics. *4) Clothing* where a person wearing different clothing may cause an automatic signature extraction method to create a widely varying signature for an individual

In this paper we use the term gait recognition to signify the identification of an individual from a sensor based approach of the subject walking. This does not mean that gait is limited to walking, it can also be applied to running or any means of activities on foot, or in other words called for activity recognition.

Activity recognition has become a very important area of research due to its application in many different areas such as health care, fitness, industrial application, security, entertainment, etc. [12, 13, 8, 2, 3]. The goal of activity recognition is to recognize and track human activities, which is also an important goal of ubiquities computing [8]. The idea of ubiquitous computing is to integrate smart phones into our environment, everyday objects and activities etc, to become assistance in our everyday lives and work [9].

The combination of gait and activity recognition will be used as an authentication service to secure smart phones from unauthorized access. Still now-a-days, smart phone users users only perform authentication at login time with either a password or pattern. Performing the last mentioned measure gives a stronger guarantee that the claimed user logging in is not a impostor but an authorized user. An issue raises that, not many systems of security requires any further measure once the user is granted access thus assuming that the user is legitimated into the system.

This paper is divided into five further sections. Section 11.2 gives an brief explanation on the implementation that has been performed onto the Samsung Nexus S smart phone to be used for gait recognition and activity. Section 11.3 describes the experiment and the technology used for data collection. Section 11.4 presents the feature extraction and analysis. Experimental results are presented in Section 11.5. Finally, Section 11.6 gives conclusion and future work.

11.2 Implementation

We have implemented a framework for activity and gait recognition for the Samsung Nexus S, which also runs on smart phones from a variety of brands (support Android OS). The application builds models and performs classification for accelerometer data collected on mobile phones. Due to the optimized algorithms applied for activity recognition and gait recognition, our application is able perform recognition and classification in real-time on the phone with-out reducing large amount of battery. Furthermore, the application provides an graphical user interface sending the real-live information of the comparison and classification to the user as seen in Figure 11.1, 11.2 and 11.3. In the enrollment mode, the user can choose how many walks needs to be performed. The more walks one chooses the more stable the reference template will be for a given user. In the authentication mode, one has only the ability to choose the length of time that is needed for authentication. Typically 10 second is enough for data retrieval. Furthermore, the smart phone does not need to be attached in a special way to the body of the individual, and can be placed wherever the subject wants.

It further allows also other biometric characteristics to be implemented and used for authentication, such as face, fingerprint, voice,knuckle and gesture recognition. The main purpose of this paper only focuses on gait and activity recognition.

11.3 Experiment

So as to obtain acceleration data we used the Samsung Nexus S smart phone as mentioned earlier. It consists of a high quality accelerometer which can measure the body motion

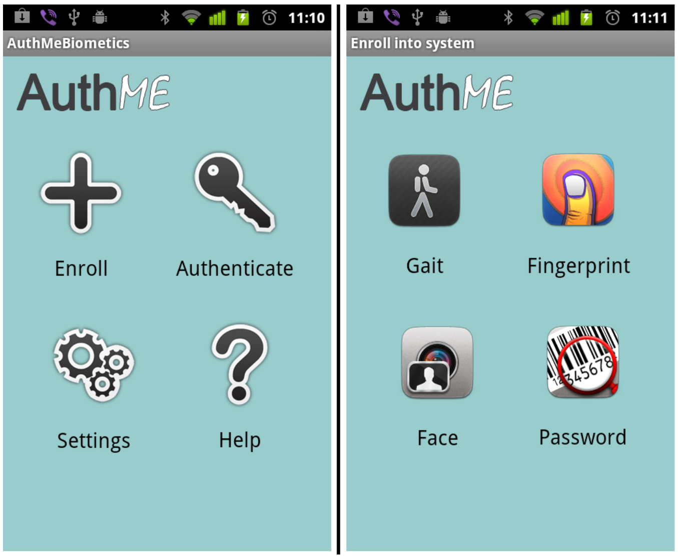


Figure 11.1: Left: The main menu of the application, Right: Enrollment and Authentication choice.

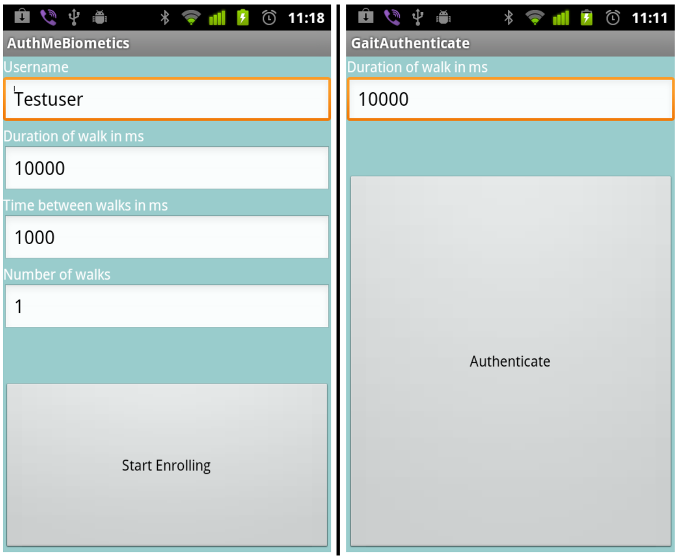


Figure 11.2: Left: Enrollment process, Right: Authentication process

in three directions (x,y,z). The acceleration range of the accelerometer is between -2g and +2g. The sampling occurs at non equidistant intervals with a frequency sampling about 150 samples per second in all three directions. The x direction indicates the vertical acceleration which does also contain the gravity. The y-acceleration corresponds to the forward-backward movement and the z-acceleration indicates the lateral acceleration.

For gait and activity recognition, we will train the phone with a number of activities that can be safely performed indoors without extra equipment. Subjects will be asked to walk with the phone for approximately 10 seconds, while the phone creates a reference template to their gait. Volunteers will then be asked to perform those activities, one at a time, while carrying the phone in their pocket. The comparison and classification will be performed on the phone. The participants will have the opportunity to observe which activity they have

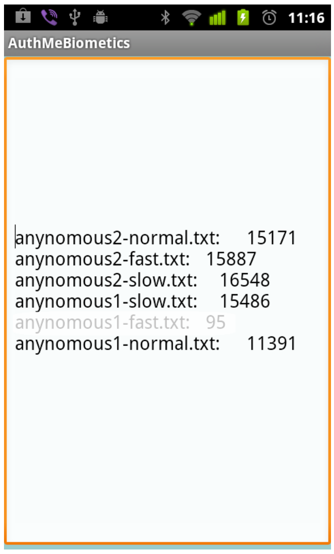


Figure 11.3: Output of the application (with comparison scores) after an authentication has been performed. The application identifies the activity by marking the text with gray colors.

been performed while carrying the phone

In the experiment we requested volunteers to execute different activities, namely normal, fast and slow walking. In total, 30 subjects participated where most of them used shoes with flat sole. All volunteers were asked to perform the three mentioned types of activities 15 times for the same fixed distance of around 29 meters for one activity. That would give 29 * 15 = 435 meters of walking for one user per session. One session includes random chosen activities (normal, fast or slow) equally distributed. The volunteers in the experiment were students and employees from all places. In addition 5 random volunteers were asked to walk one extra time per activity per session. This will cause in (5 * 16) + (25 * 15) = 455 walks in total.

11.4 Feature Extraction and Analysis

11.4.1 Extraction of Cycles from each type of walk

Each type of walk, whether is it slow, normal or fast needs now to be processed in order to create reference and probe templates for each subject. From these types of walks the repeating cycles are extracted for each person. The extraction of cycles a first step towards performance of gait and activity recognition analysis. A brief description of the steps conducted for feature extraction is given in the following:

Linear Time Interpolation: Due to the android SDK, the Nexus S only outputs data values whenever there is a change in the sensor. Therefore, the time intervals between two sample points (acceleration values) are not always equal, which requires time interpolation. This ensures that the time-interval between two sample-points will be fixed.

Filtering: Removal of noise is done by applying a weighted moving average (WMA) filter. This ensures to smoothen the signal and removes high peaks.

Cycle length estimation: From the data it is known that the cycle length is between $130 - 150$ samples. To compute the average cycle length a small subset from the center of the data is extracted and compared with other subsets of similar length. Based on the distance scores between these subsets, the average cycle length is computed.

Cycle Detection: The cycle detection starts from a minimum point $P_{start} = P_{min}$ around the center of the walk. From this point, cycles are detected in both directions. By adding the average length to P_{start}, the estimated ending point $P_{end} = P_{start} + averageLength$ is retrieved (in opposite direction: $P_{end} = P_{start} - averageLength$). The cycle end is defined to be the minimum in the interval of +/- 10% (of the average cycle length) from the estimated end point, see figure 11.4. This process will be repeated from the new end point until all cycles are detected. Finally after going through previous phases and finding the

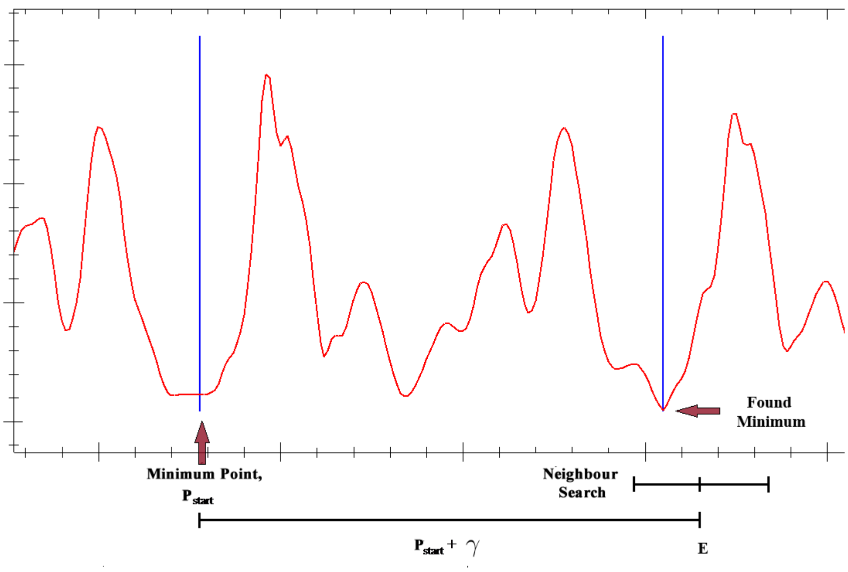


Figure 11.4: Cycle Detection

minimum points we are ready to start with the actual detection and able to find the beginning and end of each cycle. This is done by first searching cycles forward from the starting location point detected in the previous phase, and when forward searching is complete we repeat this process by searching backwards. The cycles extracted are would then be stored as shown in Figure 11.5.

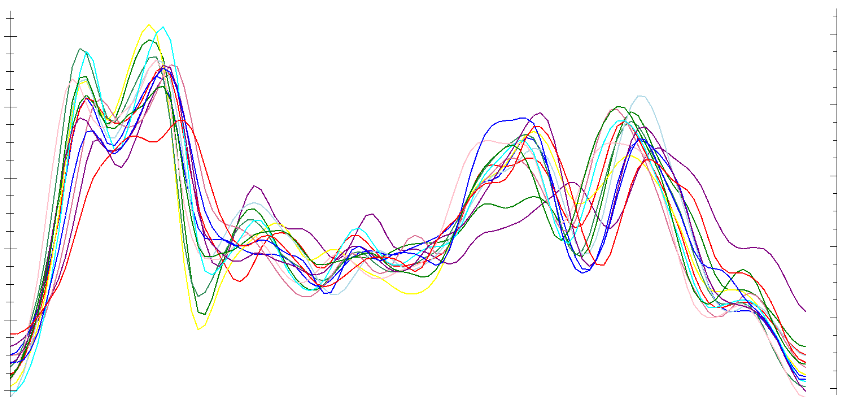


Figure 11.5: The cycles extracted from normal walk

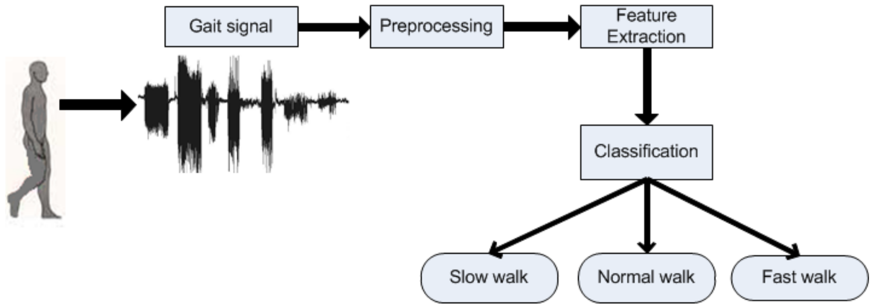


Figure 11.6: Classification of the Activities

11.4.2 Activity Recognition Analysis

Activity recognition consist of two part. First part explains how the extraction of features from the gait cycles for each walk was performed. Second part uses different classification techniques to evaluate the accuracy from the extracted features:

11.4.2.1 Features

Selection and calculation of individual features is needed for each activity performed. Feature extraction is an essential step for activity recognition. They need to be carefully chosen since they have a great influence in the result of final classification. For each of the 15 (16) walks per user we have selected four features to extract for each cycles: Standard Deviation, Minimum Value, Maximum Value, and Cyclelength. The reason why we chose these feature is because each of them output different values for different activities.

11.4.2.2 Classification

An overview of the classification is illustrated in Figure 11.6. The first step is the preprocessing, where the signal is processed by filters to remove noise, or eventually segmentation if the signal consist of more than one type of walk. The next step is the feature extraction. This is the process of extracting the most relevant information form the data segments. The features extracted passes through the classification phase. This phase classifies the data into labeled classifiers which are used to identify different human activities. One can apply different approaches for the classification, such as the support vector machine, Bayes network, neural network, etc.

The accuracy evaluation has been executed by the use of the open source software WEKA. WEKA is a collection of machine learning algorithms, and it contains tools for data pre-processing, classification, regression, clustering, association rules etc.

11.4.3 Gait Recognition Analysis

Gait recognition performance evaluation consist of also two phases. First phase consist of the gait cycle extraction from each type of walk. Second part shows how to compare features vectors against each other. This part does not apply machine learning approaches, but instead uses several distance metrics/functions. Both parts are described in more details below.

11.4.3.1 Feature Extraction

Each user performed 15 walks of different types. From each of the 15 walks the cycles are extracted as described in Section 11.4.1. For each walk a feature vector is created and consists of all extracted cycles stored in a template (either as reference or probe), denoted $C^S = \{C^S_1, ..., C^S_N\}$. This is further illustrated in Figure 11.5.

11.4.3.2 Feature Comparison

Since each feature vector template has similar length we applied several distance metrics/functions such as the Manhattan and Euclidean. Furthermore, we applied a time series analysis named the Dynamic Time Warping (DTW) which is an algorithm for measuring similarity between two sequences which may vary in time or speed.

In addition we have also applied a modified distance metric, named the Cross-DTW metric (CDM). This metric cross-compares two sets of cycles to find the best matching pair for vectors or unequal length. The algorithm is explained in more details in the following:

Cross Comparison: is used to find the most optimal and best distance score when cross-comparing two set of cycles, denoted $C^S = \{C^S_1, ..., C^S_N\}$ and $C^T = \{C^T_1, ..., C^T_M\}$. This means that each cycle in set C^S is compared to every cycle in set C^T. The comparison distances are calculated by the Cross-DTW metric (CDM). From the total number of N $\times$ M similarity distance scores gained, the minimum distance score is selected,

$$d_{min} = min\{CDM(C^S_i, C^T_j)\}$$

where i=1..N and j=1..M. The pair of cycles with the most minimum similarity score is considered the best matching pair. Thus, this best (i.e. minimum) similarity score, d_{min}, is used as the similarity score between set C^S and C^T.

The output of the CDM is called the comparison score S, where a low value of S indicates high similarity, while a high value indicates low similarity.

11.5 Results

This section is split into a section that describes the accuracy of activity recognition and the performance of gait recognition.[1]

11.5.1 Activity Recognition

With extracted features from 5 session where each session consist of one of the three different walking activities (normal, fast and slow) performed by 30 subjects we did two different evaluations; personal based and global based. We applied supervised learning approaches consisted of both training and testing data and several known algorithms. Therefore, we have split the data into training and testing set by using cross validation. Cross-validation with k-fold uses k-1 folds for training and the remaining one for training, and splits the data by choosing randomly.

Personal Cross Validation: The first performance evaluation we did was cross validation for individual-based activity recognition. This means that we look separately at each users's activity performance. Table 11.1 shows the results of classification for different classifiers used. From the results we see the great performance of distinguishing one activity from another. The best retrieved result was given by Support Vector Machine (SVM) with an accuracy of 99.59%, also an accuracy of 98.98% was achieved by RBFNetwork. These accuracy rate clearly indicates how applicable the two approaches for correctly identifying different activities performed by a subject are.

Global Cross Validation: Second test was global cross validation. In this combination we merged all data together from all 30 subjects into one file. The results are shown on Table

[1]When a user performs any activity the system first checks if it is cyclic, i.e. if cycles can be detected. If not, then the data is ignored. If a cyclic activity is detected, then the system will try to match it against one of the three known activities, meaning that any untrained (cyclic) activity will be matched incorrectly to one of the trained activities.

Table 11.1: Crossvalidation

Classifier	Personal	Global
BayesNet	97.9%	81.9%
LibSVM	99.6%	87.6%
LMT	98.1%	86.7%
MultilayerPercepton	96.77%	83.3%
NaiveBayes	97.3%	80.5%
RBFNetwork	98.9%	81.1%
RandomTree	97.9%	80.9%

11.1, third column. These results indicate how different normal, fast and slow walk are from each for all users. The LibSVM and LMT (Logistic Model Trees) performed better with an average recognition rate of 87.61% and 86.74%. Compared to personal cross validation, this clearly shows that recognition accuracies are lower.

11.5.2 Gait Recognition

Performance evaluation was performed on several settings. We calculated the equal error rates (EER) by comparing all three walking types with each other: normal against normal, slow against slow, and fast against fast. In addition we have also calculated the overall performance, i.e. to include both normal, fast and slow. The comparison approach is described in subsection 11.4.3.2 and the results retrieved are shown in this section.

One of the first performance evaluation analysis performed was to investigate the similarities of fast, normal and slow. In this test we assumed that the fast, normal and slow for the same user should be marked as a genuine trial. This means that whenever a fast reference template compares itself against either a slow or normal probe template from the same user, then we consider this as a genuine attempt. Table 11.2 shows an overview of these equal error rates.

Table 11.2: EER when comparison of normal,fast and slow for the same user is considered as a genuine attempt.

Comparison Approach	EER
Euclidean	41%
Manhattan	40%
DTW	38%
Proposed CDM	36%

These equal error rates are high and not practical for gait recognition. In this test we can verify that three types of walking are different and further *can not* assume that a slow template compared against either a normal or fast, vice versa, should be considers as a genuine attempt. This is to be compared with fingerprint recognition. Different types of walking are the same as different fingers. The index finger is not alike a thumb finger, even since they are both from the same user. That concludes the fact that the three types of walking should be considered as impostor attempt when they are compared against each other from the same user.

The second evaluation test is performed as the first mentioned. However the difference here is that we do not consider comparison of the three types of walking (slow,fast,normal) from the same user marked as a genuine attempt. Table 11.3 overviews the EER.

Comparing Table 11.2 with 11.3, we observe a great improvement where the EER went down from 36% to 7.59% using the proposed CDM. This is a very significant reduction,

Table 11.3: EER when comparison of normal,fast and slow for the same user is considered as an impostor attempt.

Comparison Approach	**EER**
Euclidean	16.0%
Manhattan	15.5%
DTW	10.3%
Proposed CDM	7.5%

where we further can conclude that dissimilar types of walk should be considered as non-genuine-attempts when comparison is performed with the same user.

Table 11.4: Performance Evaluation (EER) of Gait Recognition when looking at the comparison of normal,fast and slow separately.

Comparison Approach	**Fast**	**Normal**	**Slow**
Euclidean	13.7 %	18.3%	22.4%
Manhattan	12.5 %	17.9%	21.7%
DTW	7.6 %	10.3%	15.4%
Proposed CDM	5.7 %	12.6%	13.2%

What we observe from these three results are that by walking fast we retrieve better performance with a difference of almost to 8% to the worst. At least one valid factor plays a role. When walking fast we retrieve more information compared to slow walking. The user is in a rush and thus applies more movements in all of the three directions (x,y,z) to the body. When the subject is slow walking, he/she would have almost no acceleration in the the three directions. In a mathematically sense, we see the the standard deviation is larger from the mean when looking at the fast walking compared to slow walking. This is why the normal walking is in between.

11.6 Conclusions and future work

In this paper we described how a Samsung Nexus S smart phone can be used to perform activity recognition and gait recognition, simply by attaching it in into a pocket. An real application has been developed where it is possible to enroll user with their walking and with different activities. We have demonstrated that acceleration data collected while walking, either fast, normal or slow, have the potential to function as biometric signatures in real-life. Furthermore, we show that users can often be recognized quickly, using only 10 seconds worth of data. In addition we showed that by using the algorithms proposed for authentication, we can offer practical performance with an EER of 5.7 if the user is walking normal. Biometric gait recognition in smart phones has become and realistic and practical way of protecting the smart phone from unauthorized access.

11.7 Acknowledgment

The authors thank all participants of the data collection.

11.8 Bibliography

[1] AILISTO, H. J., LINDHOLM, M., MANTYJARVI, J., VILDJIOUNAITE, E., AND MAKELA, S. M. Identifying people from gait pattern with accelerometers. In *Proceedings of SPIE* (2005), vol. 5779, p. 7. 155

[2] BAO, L., AND INTILLE, S. S. Activity Recognition from User-Annotated Acceleration Data. *Pervasive Computing* (2004), 1–17. Available from: `http://www.springerlink.com/content/9aqflyk4f47khyjd`. 156

[3] CHOUDHURY, T., BORRIELLO, G., CONSOLVO, S., HAEHNEL, D., HARRISON, B., HEMINGWAY, B., HIGHTOWER, J., KLASNJA, P., KOSCHER, K., LAMARCA, A., LANDAY, J. A., LEGRAND, L., LESTER, J., RAHIMI, A., REA, A., AND WYATT, D. The Mobile Sensing Platform: An Embedded Activity Recognition System. *IEEE Pervasive Computing 7*, 2 (Apr. 2008), 32–41. Available from: `http://dx.doi.org/10.1109/MPRV.2008.39`. 156

[4] DERAWI, M., BOURS, P., AND HOLIEN, K. Improved cycle detection for accelerometer based gait authentication. In *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference on* (oct. 2010), pp. 312 –317. 155

[5] DERAWI, M., NICKEL, C., BOURS, P., AND BUSCH, C. Unobtrusive user-authentication on mobile phones using biometric gait recognition. In *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference on* (oct. 2010), pp. 306 –311. 155

[6] FRANK, J., MANNOR, S., AND PRECUP, D. Activity and gait recognition with time-delay embeddings. In *AAAI* (2010), M. Fox and D. Poole, Eds., AAAI Press. 155

[7] GAFUROV, D. *Performance and security analysis of Gait-based user authentication*. Ph.D. thesis, Gjøvik University College, Gjøvik, 2008. 74, 155

[8] HE, Z., AND JIN, L. Activity recognition from acceleration data based on discrete consine transform and svm. In *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on* (2009), pp. 5041 –5044. 156

[9] HUYNH, D. T. G. *Human Activity Recognition with Wearable Sensors*. Ph.D. thesis, TU Darmstadt, Darmstadt, September 2008. Available from: `http://tubiblio.ulb.tu-darmstadt.de/38560/`. ix, xi, 34, 36, 129, 130, 131, 147, 156

[10] JOHANSSON, G. Visual perception of biological motion and a model for its analysis. *Attention, Perception, and Psychophysics 14* (1973), 201–211. 10.3758/BF03212378. Available from: `http://dx.doi.org/10.3758/BF03212378`. 155

[11] KWAPISZ, J., WEISS, G., AND MOORE, S. Cell phone-based biometric identification. In *Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on* (sept. 2010), pp. 1 –7. 155

[12] KWAPISZ, J. R., WEISS, G. M., AND MOORE, S. A. Activity recognition using cell phone accelerometers. *Human Factors* (2010), 1018. Available from: `http://storm.cis.fordham.edu/~gweiss/papers/sensorKDD-2010.pdf`. 156

[13] LONG, X., YIN, B., AND AARTS, R. Single-accelerometer-based daily physical activity classification. In *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE* (2009), pp. 6107 –6110. 156

[14] MURRAY, M. P. Gait as a total pattern of movement. *American Journal of Physical Medicine 46*, 1 (1967), 290–333. Available from: `http://vibration.shef.ac.uk/doc/10175666.pdf`. 155

[15] NICKEL, C., BRANDT, H., AND BUSCH, C. Classification of acceleration data for biometric gait recognition on mobile devices. In *BIOSIG* (2011), pp. 57–66. 155

[16] NICKEL, C., BUSCH, C., RANGARAJAN, S., AND MOBIUS, M. Using hidden markov models for accelerometer-based biometric gait recognition. In *Signal Processing and its Applications (CSPA), 2011 IEEE 7th International Colloquium on* (march 2011), pp. 58 –63. 155

[17] NICKEL, C., DERAWI, M., BOURS, P., AND BUSCH, C. Scenario test for accelerometer-based biometric gait recognition. In *3rd International Workshop on Security and Communication Networks (IWSCN 2011)* (2011). 155

Appendix A

Gait Recognition for Children over a Longer Period

Abstract

In this paper a comparative investigation into the effects of time on gait recognition in children's walking has been carried out. Gait recognition has attracted considerable interest recently; however very little work has been reported in the literature which is related to gait recognition in children. It has been suggested ([13])that the gait of children does not stabilize before they are 11 years old. In this papers we will provide arguments that support this suggestion. When looking at the performance of gait recognition, which serves as an indicator for the stability of gait, we found a relationship between performance improvement and aging of children. The gait of a group of children was measured twice with a 6 months period between the two measurements. Our analysis showed that the similarity between these two measurements is significantly lower than the similarity within each of the measurements. Finally we also report the effect of gender on performance of gait recognition.

A.1 Introduction

Even though gait analysis has a long history dating back to the time of Aristotle, who studied animal locomotion using artistic works, it was much later that work on the biomechanics of human walking was carried out at the end of the 19th century [1, 17]. In recent years gait analysis has progressed rapidly with the development of more sophisticated electronics, advanced computer technology and more accurate sensors [9]. A major interest in gait analysis involves its applications to bioengineering, physiotherapy, rehabilitation, the management of medical problems affecting the locomotor system and sports performance [20, 18, 12, 21]. More recently, it has also attracted considerable attention of researchers in identification and recognition for security and safety purposes [14, 6]. Gait has a number of advantages over other forms of biometric features. For example, it is unique as each person has a distinctive walk, it is unobtrusive as gait avoids physical contact whilst collecting data unlike most other methods which involve physical touching; data can also be collected at a distance without the need for close proximity [7, 4].

For improved security, gait analysis is being used for biometric authentication and identification [11]. Currently, there are three types of systems being employed, which are machine vision based (MV), floor sensor based (FS) and wearable sensors (WS). Each type has its own unique advantages and disadvantages depending on the specific application being considered. The MV systems can be used remotely without any user interaction; however it is expensive and involves the use of background subtraction. FS based is very accurate but it is expensive to install and maintain. WS are simple, small and inexpensive devices and are not location dependent [10]. These can be readily incorporated into mobile devices such as the popular i-Phone.

For adults of both genders, considerable research has been done on gait recognition and medical applications [8, 22, 6, 5]. However, with children very little work has been reported in the literature [16, 15]. In previous studies we have reported an analysis of gait performance in children compared to adults [3] and gait analysis under special circumstances [2] such as variations in walking speed and carrying objects. In this paper we present a study on the effects of time on gait patterns in children and its relationships to gender and age. The accelerometer sensor was placed on the left side of hip. A comparative analysis of gait patterns in children and adults both male and female for the purposes of recognition and identification is presented.

A.2 Experiment Design

In this study a programmable sensor (Model GP1, see Figure A.1) purchased from Sensr (USA, `http://www.sensr.com`) was programmed and used to record the motion of the children in several walking cycles. The GP1 measures the acceleration in three perpendicular directions which will be referred to as x, y and z. Figure A.2 is an example of the output obtained from the GP1 sensor and shows the signals obtained in the x, y and z directions. These signals provided the raw data for the subsequent analysis reported in later sections of this paper. It is converted into a unique pattern for each individual for comparison. The GP1 can collect acceleration data up to $10g$ and has a sampling rate of 100 Hz per axis. Acceleration data is filtered inside the GP1 by a 2 pole Butterworth low pass filter with a cut-off frequency of 45 Hz [19]. The device has a USB interface for transferring data and a 1 Mbyte memory for storage purposes. An overview of the specification of the Sensr GP 1 is given in Table A.1.

Figure A.1: SENSR GP1 Device

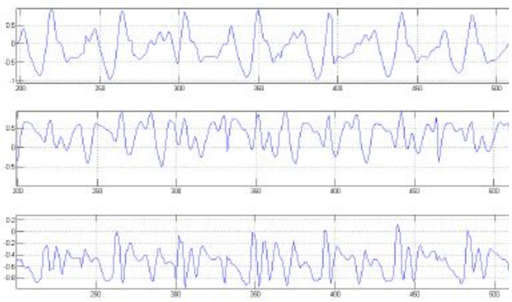


Figure A.2: (x,y,z) Acceleration Output

Item	Specification
Size	3.935″ x 2.560″ x 1.140″
Weight with batteries	8.25 oz
Connectivity	USB
Accelerometer type	Programmable 3 axis MEMS
Accelerometer range	Programmable $\pm 2.5g$, $\pm 3.3g$, $\pm 6.7g$, $\pm 10g$
Sampling rate	100 Hz per axis
Memory type	Non-volatile EEPROM
Memory size	1 MByte
Device Temperature Range	-20^oC to + 80^oC

Table A.1: Partial Specification of the GP1 Sensor.

In this study, 46 children (31 boys and 15 girls) with ages ranging between 5 to 16 years participated. Ethical approval was obtained from the school principal, the university's ethical approval committee and parents of the children. For each child, the parents formally approved participation in the study by signing a standard University approval consent form prior to volunteering. The criteria set for the child to take part of this study were that they should have no previous history of injury to the lower extremities within the past year, and no known musculoskeletal or neurological disease.

The Sensor was attached to left side of the hip (see Figure A.3) because previous studies have shown that the hip is the most stable position compared to leg, arm and other body positions. Volunteers were told to walk normally for a distance 17.5 meters in a carpeted hall on a flat surface in bare feet (see Figure A.4). At the end of the hall section the volunteers waited 5 seconds, turned round, waited 5 seconds and then walked back again.

Figure A.3: The Sensor Position

Figure A.4: Walking Hall

This procedure was repeated twice and the data recorded was transferred to a PC for storage and analysis. The detailed sequence is as follows.

1. Connect to PC and initialise
2. Attach to the belt on the left hand side of the hip
3. Press the start recording button
4. Wait for 5 seconds
5. Walk 17.5 meters from one end of hall section to the other
6. Stop and wait for 5 seconds
7. Turn around and wait for 5 seconds
8. Walk back 17.5 meters wait for 5 seconds and turn around
9. Repeat procedure

After walking twice the sensor was detached from the volunteer, connected to the computer and the data inside the GP1 device was downloaded and stored and the filed was named appropriately.

The main experiment was carried out over a time period of 6 months. First experiment was performed in September 2010 and the second was performed in March 2011. There were 20 volunteers who participated in the long term experiment out of an initial group of 46. In September 2010, each subject did 2 sessions, whilst 16 sessions were performed in March 2011. This means that each subject participated in 18 sessions in total.

A.3 Feature Extraction

The raw data retrieved from the Sensr sensor needs to be processed in order to create robust templates for each subject. The feature extraction steps are based on the work of [8].

Preprocessing: First we apply *linear time interpolation* on the three axis data (x,y,z) retrieved from the sensor to obtain an observation every $\frac{1}{100}$ second since the time intervals between two observation points are not always equal. Another potential problem is that the acceleration data from the sensor includes some noise. This noise is removed by using a *weighted moving average* filter (WMA) . The formula for WMA with a sliding window of size 5 is given in Equation A.1.

$$\frac{(a_{t-2}) + (2a_{t-1}) + (3a_t*) + (2a_{t+1}) + (a_{t+2})}{9}, \tag{A.1}$$

where a_t is the acceleration-value in position t. The current value we are located at are given weight 3, the two closest neighbors weight 2 and the next two neighbors weight 1.

Finally we calculate the resultant vector or the so-called magnitude vector by applying the following formula,

$$r_t = \sqrt{x_t^2 + y_t^2 + z_t^2}, t = 1, ..., N$$

where r_t, x_t, y_t and z_t are the magnitudes of resulting, vertical, horizontal and lateral acceleration at time t, respectively and N is the number of recorded observations in the signal.

Cycle Detection: From the data it is known that one cycle-length varies between $80 - 140$ samples depending on the speed of the person. Therefore we need to get an estimation of how long one cycle is for each subject. This is done by extracting a small subset of the data and then comparing the subset with other subsets of similar lengths. Based on the distance scores between the subsets, the average cycle length is computed, as can be seen in Figure A.5.

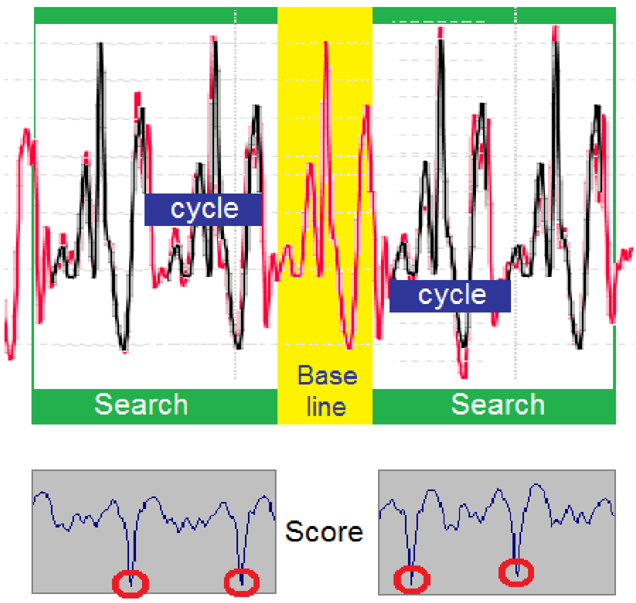


Figure A.5: The yellow baseline area indicates the subset with 70 samples that are extracted, the green area is the search area where the baseline is compared against a subset of the search area. The 4 black subgraphs are the baseline at those points that has the lowest distance with the search area subsets, and the difference between them (blue area) indicate the cycle length [8].

The cycle detection starts from a minimum point, P_{start}, around the center of the walk. From this point, cycles are detected in both directions. By adding the average length, denoted γ to P_{start}, the estimated ending point $E = P_{start} + \gamma$ is retrieved (in the opposite direction: $E = P_{start} - \gamma$). The cycle end is defined to be the minimum in the interval Neighbour Search from the estimated end point. This is illustrated in Figure A.6. This pro-

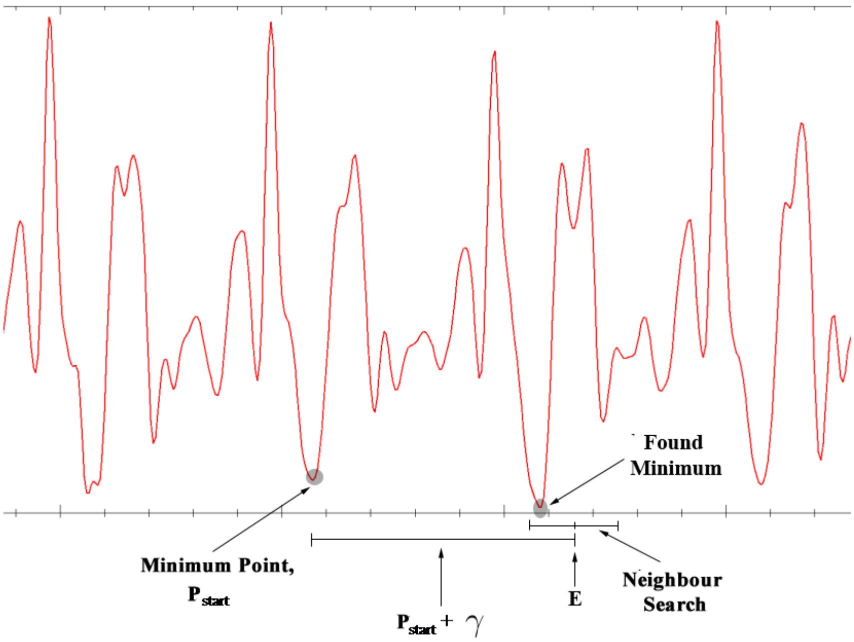


Figure A.6: Cycle detection showing how each cycle (i.e the steps) in the resultant vector is automatically detected [8].

cess is repeated from the new end point, until all the cycles are detected. The end point in the Neighbour Search is found by starting from point E. From this point we begin searching 10% of the estimated cycle length, both before and after E for the lowest point. When the minimum point is found we store it into an array and we begin searching for the next minimum point by adding the length of one estimated cycle. When forward searching is complete we repeat this phase by searching backwards so all steps in the data are identified. We will therefore end up with having an array containing start/end index for each step. These points will therefore be used for the extraction of cycles, as illustrated in Figure A.7.

Template Creation: Before we create the feature vector template, we ensure that cycles that are very different from the others are skipped. This is done by taking each cycle and calculating its distance compared to every other cycle by using dynamic time warping (DTW),

$$dtw_{i,j} = dtw(cycle_i, cycle_j)$$

where i = 1..N and j = 1..N, which means that we will get a symmetrical N $\times$ N matrix. From this point, we calculate all the averages of one specific cycle to all others.

$$d_i = \frac{1}{N-1} \sum_{j \neq i} dtw_{i,j}$$

Thereafter we calculate the average of the calculated averages,

$$\mu = \frac{1}{N} \sum_{i} d_i$$

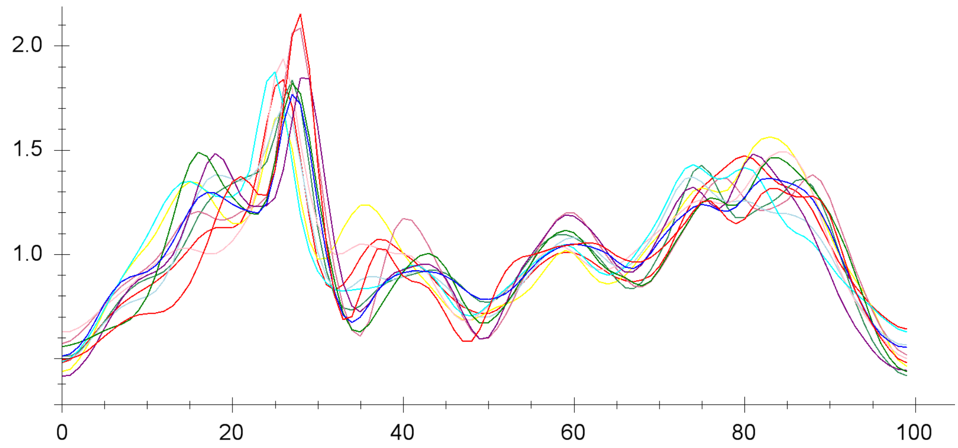


Figure A.7: The cycles have been extracted by taking starting and ending point for each step. Both these points are minimum points from the resultant-vector data set.

which therefore will be the total average. Now we will have the opportunity to see how much deviation exists from one cycle to another. Thus, the standard deviation, μ, is calculated and to use a realistic border we will accept cycles that are within 2σ of difference from the total average

$$d_i = [\mu - 2\sigma; \mu + 2\sigma]$$

The 2σ is used to process trial and error. If a lower limit was chosen, we might have ended up skipping too many cycles, while a higher limit would lead to accepting too many cycles.

When all odd cycles are removed, we create the feature vector. In previous work [10], researchers used the average cycle as a feature vector. That was computed by combining all the cycles (which were normalized) into one average median cycle. In this paper all of the extracted cycles are stored as a template for one subject, denoted $C^S = \{C_1^S, ..., C_N^S\}$ where each cycle i = 1..N is normalized to a length of *k* observations; in our case *k = 100*.

A.4 Feature Vector Comparison

A distance metric, named the cyclic rotation metric (CRM) with small changes, is applied [8]. This metric cross-compares two sets of cycles with a cyclic-rotation mechanism to find the best matching pair:

Cross Comparison: is used to find the most optimal and best distance score when cross-comparing two set of cycles, denoted $C^S = \{C_1^S, ..., C_N^S\}$ and $C^T = \{C_1^T, ..., C_M^T\}$. This simply means that each cycle in the set C^S is compared to every cycle in the set C^T. The comparative distances are calculated by the cyclic rotation metric (CRM). From the total number of N $\times$ M distance scores calculated, the minimum score is selected,

$$d_{min} = min\{CRM(C_i^S, C_j^T)\}$$

where i=1..N and j=1..M. The pair of cycles with the most minimum similarity score is considered the best matching pair. Thus, this best (i.e. minimum) similarity score, d_{min}, is used as the similarity score between set C^S and C^T.

Cyclic Rotation Metric (CRM): is a metric that compares a reference cycle and an input cycle with each other. The reference cycle, i.e. C_i^S, which is compared against the input cycle, i.e. C_j^T, is stepwise cyclical rotated. After each rotation the new distance is calculated using the Manhattan distance. This is repeated until the input template has done a full rotation, then the lowest distance value is kept:

$$d(C_i^S, C_j^T) = min_{w=1..k}\{Manh(C_i^S, C_{j(w)}^T)\}$$

The reason why we use the Manhattan distance when rotating is due to the fact that Manhattan runs fast. Furthermore the cyclic rotation is done to minimize the problem when local extremes among the cycles we create for each input are located at different locations.

A.5 Analysis and Results

In this section we will present the analysis performed and results. Three different tests have been performed and these are as follows:

1. The first test analyzes the performance of gait and how it varies with the age of the children.
2. The second test analyzes the performance of gait and studies its variations over time, with a 6 months interval measurements.
3. The third test analyzes and compares the performance of gait between boys and girls.

As mentioned in a previous study by [13], it was suggested that the gait of children does not stabilize before they are 11 years old. In order to test this hypothesis, we have split the set of the 46 children into three groups. The first group consisted of 17 children that are at most 10 years old. The second group consisted of the 11 children in our experiment that are only 10 years old, whilst the third group consisted of 18 children that were between 11 - 16 years old. The split was done in this way because the size of the three groups is more or less equal. We do realize that the number of children in each of the three data sets is rather small, which influences the statistical significance of the results negatively. Nevertheless we want to present the results of our analysis on all three groups as an indication of the performance.

The data used for the analysis is the collected gait data from March 2011, i.e. all of the participants contributed 16 data samples for the analysis. The resulting EER values are given in Table A.2 for each of the three age groups. We also included the analysis results for the case where the group of 46 children was not split. The resulting EER can be found in the columns "All against All".

	5-9 years	**10 years**	**11-16 years**	**All against All**
Manh.+Rotation	16.12	13.74	13.21	14.23

Table A.2: EER Performance results in % on the collected dataset due to age.

From the results in Table A.2 we see that with increasing age the EER value decreases, indicating an increase in the stability of the walking of children with increaing age. This seems to confirm the suggestion from [13]. In order to test this suggestion further we tested how the walking of children would change over time. As mentioned in Section A.2 do we have gait data samples from 20 children who participated in the experiment in both September 2010 and in March 2011. In September 2010 each of the 20 children provided only 2 gait data samples, but in March 2011 each of them provided 16 data samples. Of these 20 children, 18 were below 11 years old, one was exactly 11 years old and one who was 14 years old.

We have determined the EER for each of these periods separately and we see in Table A.3 that the resulting EER values are rather similar: 18.88% for September 2010 and 18.94%

for March 2011. In order to see if the gait has developed over time we also added a test where the template was created with the September 2010 data, while the test data came from the March 2011 data. From Table A.3 we see that the EER value increases significantly from approximately 18.9% to 34.02%. This indicates a major change in the way of walking of these children, confirming the suggestion from [13] once again.

	September 2010	**March 2011**	**6 Months**
Manh.+Rotation	18.88	18.94	34.02

Table A.3: EER Performance results in % on the collected dataset due to time.

Although the number of participants in the tests is rather low, we can still clearly see a change of performance over time. We see that one group of children measured twice, with 6 months interval between measurements, has a large change in their way of walking, while we on the other hand there is also an increased stability in walking with growing age. Both these facts support the suggestion that the walking of children stabilizes around 11 years as Kyriazis suggested in [13].

A final test was performed to see if there are differences in gait recognition between boys and girls. The results can be found in Table A.4. We know from Section A.2 that the number of boys was more than twice the number of girls in the experiment conducted in March 2011. In order to make the results comparable we have used the gait data from all 15 girls and randomly selected 15 boys. The distance metric used was again the Manhattan with Rotation metric. The slightly lower EER for girls (13.44% compared to 14.86%) indicates a that the gait of female subjects is slightly more stable than the gait of male subjects.

The result in Table A.4 for the boys is based on a random selection of 15 out of the available 31 boys. In order to make the result independent of the selected boys, this random selection has been performed 100 times and the presented performance is the average over these 100 results.

	Males	**Females**
Manh.+Rotation	14.86	13.44

Table A.4: EER Performance results in % on the collected dataset over time due to gender.

A.6 Conclusions

As far as we know there are no published results on the stability of gait for young children, except from the suggestion in [13]. In this paper we have given evidence indicating the correctness of that suggestion. It has been shown that as the children get older their gait becomes more stable and that there is a large difference between the gait of a group of 20 young children measured six months apart; this indicates that the gait of children is still developing at these young ages.

In addition, a comparison was carried out between the stability of gait from girls and boys and it was found that the female gait was slightly more stable as indicated by a lower EER.

Whilst the results presented in this study are interesting and in line with previous suggestions, a more comprehensive study with a higher number of participants is required to confirm the results described in this paper. In addition, research on the stability of gait from adults over a longer period of time is needed to compare against the results presented in this paper.

A.7 Acknowledgments

The authors would like to thank all the (anonymous) participants in this experiment. The writing of this article would not have been possible without their effort in the data collection phase.

A.8 Bibliography

[1] ARISTOTLE. *On the Gait of Animals*. Kessinger Publishing, 2004. 167, 177

[2] BALISANE, H., DERAWI, M. O., BOURS, P., WAQAR, A., AND TWIGG, P. Gait recognition in children under special circumstances. In *Security and Communication Networks (IWSCN), 2011 2nd International Workshop on* (2011). 167

[3] BALISANE, H., DERAWI, M. O., BOURS, P., WAQAR, A., AND TWIGG, P. Performance of gait recognition in children's walking compared to adults. In *Security and Communication Networks (IWSCN), 2011 2nd International Workshop on* (2011). 167, 188, 189, 190

[4] BENABDELKADER, C., CUTLER, R., NANDA, H., AND DAVIS, L. S. Eigengait: Motion-based recognition of people using image self-similarity. In *Proceedings of the Third International Conference on Audio- and Video-Based Biometric Person Authentication* (London, UK, 2001), AVBPA '01, Springer-Verlag, pp. 284–294. Available from: `http://portal.acm.org/citation.cfm?id=646073.677457`. 167

[5] BOUCHRIKA, I., AND NIXON, M. Exploratory factor analysis of gait recognition. In *Automatic Face Gesture Recognition, 2008. FG '08. 8th IEEE International Conference on* (September 2008), pp. 1 –6. 167, 187

[6] BOURS, P., AND SHRESTHA, R. Eigensteps: A giant leap for gait recognition. In *Security and Communication Networks (IWSCN), 2010 2nd International Workshop on* (May 2010), pp. 1 –6. 167, 178, 180, 181, 188, 190

[7] CHENG, M.-H., HO, M.-F., AND HUANG, C.-L. Gait analysis for human identification through manifold learning and hmm. In *Motion and Video Computing, 2007. WMVC '07. IEEE Workshop on* (February 2007), p. 11. 167, 177

[8] DERAWI, M., BOURS, P., AND HOLIEN, K. Improved cycle detection for accelerometer based gait authentication. In *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference on* (October 2010), pp. 312 –317. xi, 167, 170, 171, 172, 178, 181, 182, 188, 190, 191

[9] GAFUROV, D., HELKALA, K., AND SNDROL, T. Gait recognition using acceleration from mems. In *Availability, Reliability and Security (ARES 2006), The First International Conference on* (April 2006), pp. 432–439. 167, 177

[10] GAFUROV, D., SNEKKENES, E., AND BOURS, P. Gait authentication and identification using wearable accelerometer sensor. In *Automatic Identification Advanced Technologies, IEEE Workshop on* (June 2007), pp. 220–225. 167, 172

[11] GAFUROV, D., SNEKKENES, E., AND BUVARP, T. E. Robustness of biometric gait authentication against impersonation attack. In *OTM Workshops (1)* (2006), R. Meersman, Z. Tari, and P. Herrero, Eds., vol. 4277 of *Lecture Notes in Computer Science*, Springer, pp. 479–488. 167, 177, 188

[12] JOVANOV, E., MILENKOVIC, A., OTTO, C., AND DE GROEN, P. A wireless body area network of intelligent motion sensors for computer assisted physical rehabilitation. *Journal of NeuroEngineering and Rehabilitation 2*, 1 (Mar. 2005), 6+. Available from: `http://dx.doi.org/10.1186/1743-0003-2-6`. 167

[13] Kyriazis, V. Temporal gait analysis of children aged 9-10 years. *Journal of Orthopaedics and Traumatology 3* (2002), 31–34. Available from: http://dx.doi.org/10.1007/s101950200025. 167, 173, 174, 178, 181, 182

[14] Mantyjarvi, J., Lindholm, M., Vildjiounaite, E., Makela, S.-M., and Ailisto, H. Identifying users of portable devices from gait pattern with accelerometers. In *Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP '05). IEEE International Conference on* (March 2005), vol. 2, pp. ii/973 – ii/976 Vol. 2. 167, 177

[15] Oeffinger, D., Brauch, B., Cranfill, S., Hisle, C., Wynn, C., Hicks, R., and Augsburger, S. Comparison of gait with and without shoes in children. *Gait & Posture 9*, 2 (1999), 95 – 100. Available from: http://www.sciencedirect.com/science/article/B6T6Y-3WM59K1-2/2/3bb8b2c2146a23e175cc95434ec19de7. 167, 178, 187

[16] Pascoe, D., Pascoe, D., Wang, Y., Shim, D., and Kim, C. Influence of carrying book bags on gait cycle and posture of youths. In *Ergonomics* (1997), vol. 40, pp. 631–641. 167, 178

[17] Pitkin, M. R. *Biomechanics of Lower Limb Prosthetics*. Springer, 2009. 167, 187

[18] Salehi, M., and Razzazi, M. A sensor-based framework for detecting human gait cycles using acceleration signals. In *Proceedings of the 17th international conference on Software, Telecommunications and Computer Networks* (Piscataway, NJ, USA, 2009), SoftCOM'09, IEEE Press, pp. 328–332. Available from: http://portal.acm.org/citation.cfm?id=1719770.1719836. 167

[19] Sensr. Gp1 programmable accelerometer user manual. www.sensr.com, 2007. 168, 178, 188

[20] Ying, H., Silex, C., Schnitzer, A., Leonhardt, S., and Schiek, M. Automatic step detection in the accelerometer signal. In *Proceedings of the 4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007)* (2007). 167, 177

[21] Yoshida, T., Mizuno, F., Hayasaka, T., Tsubota, K., Wada, S., and Yamaguchi, T. Gait analysis for detecting a leg accident with an accelerometer. *Distributed Diagnosis and Home Healthcare 0* (2006), 43–46. 167

[22] Yu, S., Tan, T., Huang, K., Jia, K., and Wu, X. A study on gait-based gender classification. *Image Processing, IEEE Transactions on 18*, 8 (August 2009), 1905 –1910. 167, 177, 187

Appendix B

Performance of Gait Recognition in Children's Walking Compared to Adults

Abstract

In this paper the first known results on gait recognition in children's walking are presented. All research on gait recognition has so far focused on adult walking, mostly under normal conditions, but sometimes under special circumstances. So far some papers have only mentioned that children's walking was most likely different from adult walking, but no scientific data was available to prove or disprove this statement.

In this paper we will show that the performance degradation for children's walking compared to adult walking is approximately 100%. In comparable settings we reached a 6.21% Equal Error Rate (EER) for adult gait recognition, while for children's walking we only reached an EER of 12.69%.

B.1 Introduction

Gait analysis has attracted considerable attention in recent years and can be defined as the systematic study of human walking [13, 6, 20, 14]. However, the subject of gait analysis is not a new field and has been around since the 17th century. For example, Aristotle pioneered gait analysis and a number of his artistic works are available on the gait analysis of animals [3]. The Italian scientist, Borelli also in the 17th Century had a significant interest in biomechanics, in particular animal locomotion and was the first to suggest contractile movement of muscles, thus contributing to modern principles of scientific investigation [4]. In 1890 the German autonomist, Braune [1] did some pioneering work on biomechanics using lithographic cross sections of the human body and published in a book a chapter on "biomechanical of human gait under loaded and unloaded conditions". Braune's methodology is still being used today for gait analysis.

Interest in gait analysis may be divided into two categories; biomedical applications and biometric gait identification. Gait analysis in the medical field is one of the most interesting and useful applications. For example, gait analysis is useful in the medical management of diseases that affect the locomotors system. It has been used for carrying out detailed diagnoses and subsequent optimal treatment for illnesses such as Parkinson's disease [28] which is associated with a reduction in the co-ordination between locomotion and the respiratory system.

Gait analysis is being investigated for the purposes of improved security for biometric authentication and to identify users [17]. This can be divided into three main categories: Machine Vision based (MV), Floor Sensor based (FS) and Wearable Sensor based (WS) analyses [27, 21, 23, 18, 9, 11].

Gait analysis had been widely studied in males and females, elderly people and adults. There are significant differences in the structural characteristics of males and females in the human species. Yu et al [29] showed that humans of different genders can be recognized from gait information; they carried out numerical analysis of gait information and various contributions of body components such as head and hair, back, chest and legs. They also

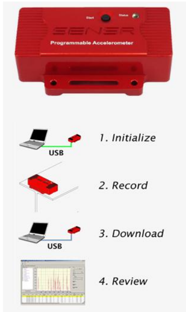


Figure B.1: GP 1 Sensor from Sensr, http://www.sensr.com.

looked at gender differences in Asians and Europeans in a controlled environment. However, the analysis is not readily translatable to real situations where gait data is affected by various factors such shoes, clothing and carrying objects.

In the past few decades the human population of elderly citizens has increased significantly placing increased demands on families and carers. Therefore to reduce costs, the use of sensors and monitors will enable information regarding the activities and movements of elderly subjects to be monitored remotely so that interventions can be carried out in case of emergencies such as a fall. Real time gait information can be gathered and assessed by family and carers, and modern technologies such as mobile devices make them non-intrusive and highly valuable. Purwar et al have investigated activity monitoring using real time tri-axial accelerometer for fall detection from gait analysis data [25].

Numerous biometric and biomedical studies in gait analysis in adults have been carried out [15, 7, 5, 12, 8]. However, very few studies have been carried out in children. Sutherland et al [26] investigated gait development in children looking at the development of mature walking. Oeffinger et al [22] did a comparison of gait analysis in children with and without wearing shoes. They found that significant differences existed in kinematic, kinetic and temporal spatial data in gait patterns. Another study [24] investigated the influence of carrying book bags on gait cycle in children and found that the gait cycle was modified when children carried bags.

This paper describes, to our best knowledge, the first investigation into gait recognition in children using a body worn sensor. An accelerometer sensor has been placed on the left side of the hip and is used for collecting information for gait recognition. Using the gait data of acceleration of the signal from the walking children, a cycle has been detected and analyzed for recognition purposes. From [16] we know that the gait pattern of children changes until the age of 11, when it becomes more or less stable. Moreover, from the age of 10 only small changes occur in the walking pattern. So it will not only be relevant to investigate the performance of gait recognition from children, but also see it in relation to the performance for adults.

B.2 Experiment design and data analysis

In this study a programmable sensor (Model GP1, see Figure B.1) purchased from Sensr (USA, `http://www.sensr.com`) was programmed and used to record the motion of the children in several walking cycles [14]. The GP1 measures the acceleration in three perpendicular directions which will be referred to as x, y and z. Figure B.2 shows an example of the output of the sensor. The GP1 can collect acceleration data between $\pm 2.5g$ to $\pm 10g$ and has a sampling rate of 100 Hz per axis. Acceleration data is filtered inside the GP1 by a 2 pole Butterworth low pass filter with a cut-off frequency of 45 Hz [2]. The device has a USB interface for transferring data and a 1 Mbyte memory for storage purposes. An overview of the specification of the Sensr GP 1 is given in Table B.1.

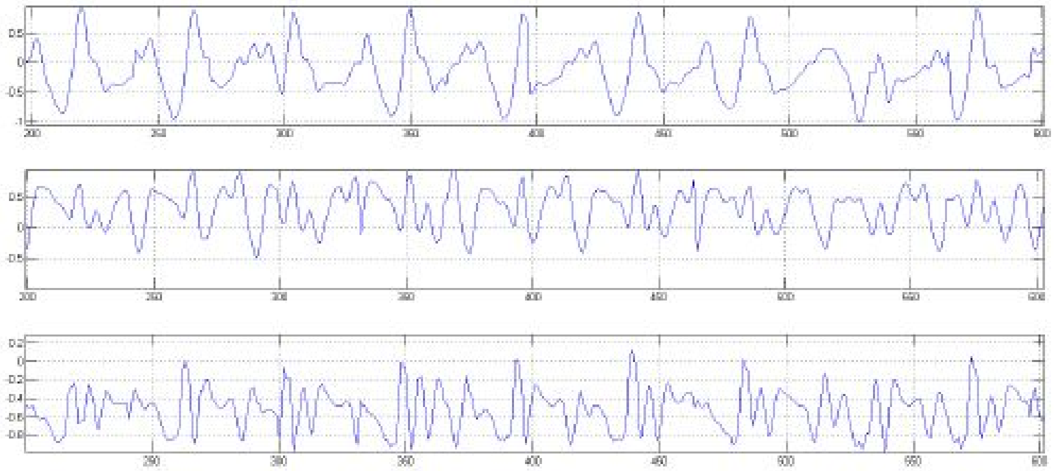


Figure B.2: Output example of the GP1 sensor.

Item	Specification
Size	3.935″ x 2.560″ x 1.140″
Weight with batteries	8.25 oz
Connectivity	USB
Accelerometer type	Programmable 3 axis MEMS
Accelerometer range	Programmable $\pm 2.5g$, $\pm 3.3g$, $\pm 6.7g$, $\pm 10g$
Sampling rate	100 Hz per axis
Memory type	Non-volatile EEPROM
Memory size	1 MByte

Table B.1: Partial Specification of the GP1 Sensor.

Age	5	6	7	8	9	10
Number of Children	1	1	2	4	7	11
Age	11	12	13	14	15	16
Number of Children	4	3	2	4	1	3

Table B.2: Age distribution of participants.

B.2.1 Experiment design

In this study, 43 children (29 male and 14 female) participated, with ages ranging from 5 to 16 years. The average male participant was 11.3 years old, while the female participants were on average 9.0 years old. Detailed information on the number of participants of a certain age is given in Table B.2. Approval was obtained from the school principal, the university's ethical approval committee and parents of the children. For each child the parents formally approved participation in the study by signing a standard University approved consent form prior to volunteering. The criteria set for the child to take part in this study were that they should have no previous history of lower extremity injury occurring within the past year, and no known musculoskeletal or neurological disease. Height and weight measurements were also taken. These measurements are not used however in the analysis presented in this paper.

The GP1 sensor was attached to a belt and positioned on the left hand side of the hip. Volunteers were asked to walk normally for a distance of approximately 17.5 meters in a carpeted hall on a flat surface without shoes. At the end of the hall the volunteers waited 5 seconds, turned round, waited 5 seconds more and then walked back. They repeated this procedure four times. The recorded data was then transferred to a PC for storage and analysis and the participants repeated the same procedure again. In total, each of the participants walked the full length of the hallway $2 \cdot 4 \cdot 2 = 16$ times. In the remainder of this paper we will refer to a *walk* as the data collected from walking the full length of the hallway one time. In other words, the data of each participant represents 16 walks.

B.2.2 Data preprocessing and analysis

As is displayed in the title of this paper, the objective of the analysis is to determine the performance of gait recognition in children's walking compared to adults. In this section we will analyze the walking data from the children that participated in the experiment to determine their gait recognition performance. These results will later be compared to a similar data set collected on adult walking.

As mentioned before, each participant walked in two different sessions and each session was downloaded as a separate file to the PC. Each of these files contained the data of 8 walks, each again separated by standing still, turning and again standing still. In each file the data representing a walk could be differentiated from standing still by looking at the variation in the data over a 50 sample period (representing 0.5 second). Also the turning could be removed from the relevant walking data, not by looking at the variation in the data but at the duration of the activity: while turning took only a brief moment, a full walk of the hall took at least 10 seconds (i.e. at least 1000 samples). The data from each collected file was thus split into 8 separate files, where each file contained a single separated walk of the hall.

Using the above method the originally $43 \cdot 2 = 86$ collected files were split into $86 \cdot 8 = 688$ files, where each file contained the data of exactly one walk. Each file was labeled in such a way that participant, session number (1 or 2) and walk within session (1..8) was identifiable from the filename. Each file contained 4 columns, representing respectively the time, the x-acceleration, the y-acceleration and the z-acceleration. The values in the time column were the original values from the collected files. From one row to the next the time value increased by 0.01 because the sampling rate was 100 samples per second.

Each of the files containing the data of a single walk were processed next using the Average Cycle Method (ACM). The ACM (see [5] for details) has been applied to the collected data. In our analysis in step 1 of the ACM, the noise was reduced by using the Weighted Moving Average (WMA) filter of length 5 and weights $(\frac{1}{9}, \frac{2}{9}, \frac{3}{9}, \frac{2}{9}, \frac{1}{9})$. The detection of cycles in step 2 of the ACM was done using the Salient method from [19]. Before creating the average cycle, all detected cycles in each walk have been normalized to 100 samples. Three different methods were used to create an average cycle: (1) median, (2) mean, and (3) Dynamic Time Warping (DTW). Suppose that N cycles were detected in a walk: $c_i = (c_i^1, c_i^2, \ldots, c_i^{100})$ for $i = 1..N$. When creating the median or mean average cycle, then the average cycle c is defined as $(c_1, c_2, \ldots, c_{100})$, where $c_i = median(c_1^i, c_2^i, \ldots c_N^i)$ or $c_i = mean(c_1^i, c_2^i, \ldots c_N^i)$ for $i = 1..100$. The DTW average is calculated in the following way; the average DTW distance between each available cycle c_i and the remaining available cycles c_j, where $j = 1..N$ and $j \neq i$, is calculated and the cycle with the least average DTW distance to the remaining available cycles has been selected as the DTW average cycle, so $c = c_i$ for some $i \in \{1, 2, \ldots, N\}$. In the case of median and mean average cycle, the resulting cycle is created from the available cycles, while in case of the DTW average, one of the available cycles is selected as the average cycle.

The three average cycles that are created in these ways were stored separately as a reference template (results shown in the first 3 columns of Table B.3), in addition to a reference template consisting of all 3 different averaged cycles (results shown in the fourth column of Table B.3). Besides that, in our analysis we also followed the work of Gafurov et al.

	Mean	Median	DTW	All 3	None
Euclidean	27.30	25.77	32.01	24.92	18.93
Manhattan	27.31	24.59	30.45	24.38	18.51
Manh.+Rotation	27.26	22.20	24.17	22.54	16.94
DTW+Rotation		21.95			12.69

Table B.3: EER Performance results in % on the collected dataset.

[10] where all detected cycles were used separately without creating an average cycle. The results for this particular method of analysis are shown in the last column of Table B.3.

Various distance metrics have been applied to find genuine and impostor scores and from that, the Decision Error Trade-off (DET) curve has been drawn and the EER has been determined. Besides the ordinary Euclidean and Manhattan distance we also used Dynamic Time Warping (DTW) as a distance metric. Both Manhattan distance and DTW have been applied in combination with the rotation method as described in [8]. Details can be found in Section B.3.

B.3 Results

In this section we will present the results of the analysis. The results from performing the analysis as described in section B.2.2 are presented in Table B.3. In this table the columns represent various averaging methods where the last column (None) represents using the separate cycles as described in [10]. The rows represent the various distance metrics that we applied.

From this table a few things are clear; first of all, using the median to create the average cycles seems to perform better than the other two averaging methods, and using all three averages does not improve the results significantly. We do however see that the method from Gafurov [10] gives the best results for each particular distance metric. Moreover, the best performance result is then reached for combining this method with the DTW+Rotation distance metric.

The results should not only be considered on their own; as mentioned previously, the data is collected using young children as volunteers and walking characteristics might not be as stable with children as it is with adults. We therefore need to compare these results to equivalent results on data collected on adults. As we do not have data available with the same sensor from adults, we have chosen to use the database that was also used in [5, 8]. This data is collected with a sensor that also collected 100 samples per second and a fixed acceleration range from -6g to +6g. The particular dataset contains data from 60 adults comprising 12 walking samples per adult, collected in 2 different sessions. The data from this dataset is analyzed in the same way as the data set of the young children, meaning we apply the same noise reduction (WMA filter), cycle detection (salient method), and normalization (to 100 samples per cycle) as is described in Section B.2.2. It is clear from Table B.3 that the methods used by Gafurov et al. [10] gives the best performance, and consequently we only applied the further analysis using this method. We applied the same distance metrics to the dataset of adult volunteers and found the following results as in Table B.4. In this table the performance degradation is defined as follows; if the performance EER for children's walking is n% and for adults m%, then we define the performance degradation as: $\frac{n-m}{m} \cdot 100\%$

From Table B.4 we can see that the performance degradation due to the less stable walking of young children is between 67 and 140%. Roughly speaking we can see that the performance degradation is 100% when we look at the optimal performance, i.e. when combining the Dynamic Time Warping distance with rotation of the cycles.

As mentioned in [16], the gait of children has not stabilized before they are 11 years old. In order to test this we have split the set of users into two groups. The first group consists of

Distance Metric	Children	Adults	Performance Degradation
Euclidean	18.93	11.20	69%
Manhattan	18.51	11.10	67%
Manh.+Rotation	16.94	7.07	140%
DTW+Rotation	12.69	6.21	104%

Table B.4: Performance comparison between adult and children's walking.

	All children	Young Children	Old Children
Euclidean	18.93	17.35	17.78
Manhattan	18.51	17.38	17.78
Manh.+Rotation	16.94	15.25	13.23
DTW+Rotation	12.69	14.11	11.40

Table B.5: EER Performance results in % on the different datasets.

26 children that are at most 10 years old, while the second group consists of the 17 children in our experiment that are at least 11 years old. Obviously both groups are too small to give statistically significant results, but nevertheless we want to present the results of our analysis on both groups. In this analysis we did use separate cycles, as explained in [10] and as used in the last column of B.3. The results are given in Table B.5, where the columns "All Children" is copied from the last column of Table B.3, the column "Young Children" represents the 26 children that are at most 10 years old, and the column "Old Children" represents the children that are at least 11 years old.

As mentioned above, the results are statistically less significant due to the small number of children in both groups, but we can see in the last row, when the distance metric is DTW + Rotation [8], then the performance for the group of youngest children is even worse than the performance for the full group of children. In that case the performance of the group of children that are at least 11 years old is better than the performance for the full group. The fact that in all other three cases the performance for both subgroups is better than the performance for the full group can be easily explained. When considering all the genuine scores and impostor scores calculated in the original analysis for the full group, we can see that each of the genuine scores either relates to the group of young children or to the group of old children. For the impostor scores this no longer holds, as there are some impostor scores in the original analysis that related to a template from a young child and a test input from an older child or vise versa. As these impostor scores are left out in the analysis of the two smaller groups it might happen (and indeed does happen) that the performance results of both smaller groups are better than the performance of the full group.

B.4 Conclusions

In this paper we presented the first known results on gait recognition in young children. When analyzing the data we could already visually see that the cycles were not as regular as we can normally see with adult walkers. This was later confirmed during the analysis of the data. Although we have seen worse performance than 12.69% previously in literature on gait recognition, we needed to see the performance in comparison to adult walking. Therefore we applied the exact same analysis methods to another dataset of similar characteristics. Though there are small differences in the number of participants and the number of walks per participant, the 100% performance degradation is a good indication of performance degradation when going from adults to young children. The walking pattern of children matures from the age of 11 [16] and looking at the ages of the participants in our experiment we see that 26 of them were younger than 11, 4 were 11 at the time of the experiment, while the remaining were older than 11.

In future research, focus on gait recognition in children's walking should be on cycle detection and finding methods to deal with the larger intra-person variation of the cycle data. Techniques that will improve the performance for gait recognition for children will then also be applicable to gait recognition for adults, thereby improving the performance for adult gait recognition too.

B.5 Acknowledgments

The authors would like to thank all the (anonymous) participants in this experiment. The writing of this article would not have been possible without their effort in the data collection phase.

B.6 Bibliography

[1] *Brockhaus' Konversations-Lexikon*. Brockhaus, 1892. 177

[2] Gp1 programmable accelerometer user manual. www.sensr.com, 2007. 168, 178, 188

[3] Aristotle. *On the Gait of Animals*. Kessinger Publishing, 2004. 167, 177

[4] Borelli, G.-A., and Bernouillii, J. *De Motu Animalium*. Kessinger Publishing, 2009. 177, 187

[5] Bours, P., and Shrestha, R. Eigensteps: A giant leap for gait recognition. In *Security and Communication Networks (IWSCN), 2010 2nd International Workshop on* (May 2010), pp. 1 –6. 167, 178, 180, 181, 188, 190

[6] Cheng, M.-H., Ho, M.-F., and Huang, C.-L. Gait analysis for human identification through manifold learning and hmm. In *Motion and Video Computing, 2007. WMVC '07. IEEE Workshop on* (February 2007), p. 11. 167, 177

[7] Degen, T., Jaeckel, H., Rufer, M., and Wyss, S. Speedy:a fall detector in a wrist watch. In *Wearable Computers, 2003. Proceedings. Seventh IEEE International Symposium on* (October 2003), pp. 184 – 187. 178, 187

[8] Derawi, M., Bours, P., and Holien, K. Improved cycle detection for accelerometer based gait authentication. In *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference on* (October 2010), pp. 312 –317. xi, 167, 170, 171, 172, 178, 181, 182, 188, 190, 191

[9] Gafurov, D., Helkala, K., and Sndrol, T. Gait recognition using acceleration from mems. In *Availability, Reliability and Security (ARES 2006), The First International Conference on* (April 2006), pp. 432–439. 167, 177

[10] Gafurov, D., Snekkenes, E., and Bours, P. Improved gait recognition performance using cycle matching. In *Advanced Information Networking and Applications Workshops (WAINA), 2010 IEEE 24th International Conference on* (April 2010), pp. 836 –841. 181, 182, 190, 191

[11] Gafurov, D., Snekkenes, E., and Buvarp, T. E. Robustness of biometric gait authentication against impersonation attack. In *OTM Workshops (1)* (2006), R. Meersman, Z. Tari, and P. Herrero, Eds., vol. 4277 of *Lecture Notes in Computer Science*, Springer, pp. 479–488. 167, 177, 188

[12] Han, J., and Bhanu, B. Individual recognition using gait energy image. *Pattern Analysis and Machine Intelligence, IEEE Transactions on 28*, 2 (February 2006), 316 –322. 178

[13] Johnson, A. Y., and Bobick, A. F. A multi-view method for gait recognition using static body parameters. In *AVBPA* (2001), J. Bigün and F. Smeraldi, Eds., vol. 2091 of *Lecture Notes in Computer Science*, Springer, pp. 301–311. 177

[14] Kale, A., Sundaresan, A., Rajagopalan, A., Cuntoor, N., Roy-Chowdhury, A., Kruger, V., and Chellappa, R. Identification of humans using gait. *Image Processing, IEEE Transactions on 13*, 9 (September 2004), 1163 –1173. 177, 187

[15] Karantonis, D., Narayanan, M., Mathie, M., Lovell, N., and Celler, B. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *Information Technology in Biomedicine, IEEE Transactions on 10*, 1 (January 2006), 156 –167. 178

[16] Kyriazis, V. Temporal gait analysis of children aged 9-10 years. *Journal of Orthopaedics and Traumatology 3* (2002), 31–34. Available from: `http://dx.doi.org/10.1007/s101950200025`. 167, 173, 174, 178, 181, 182

[17] Mantyjarvi, J., Lindholm, M., Vildjiounaite, E., Makela, S.-M., and Ailisto, H. Identifying users of portable devices from gait pattern with accelerometers. In *Acoustics, Speech, and Signal Processing, 2005. Proceedings. (ICASSP '05). IEEE International Conference on* (March 2005), vol. 2, pp. ii/973 – ii/976 Vol. 2. 167, 177

[18] Middleton, L., Buss, A., Bazin, A., and Nixon, M. A floor sensor system for gait recognition. In *Automatic Identification Advanced Technologies, 2005. Fourth IEEE Workshop on* (October 2005), pp. 171 – 176. 177, 187

[19] Nickel, C., Derawi, M. O., Busch, C., and Bours, P. Field test of accelerometer-based biometric gait recognition. In *3rd International Workshop on Security and Communication Networks (IWSCN)* (2011). 180, 190

[20] Nixon, M. S., Tan, T. N., and Chellappa, R. *Human Identification Based on Gait*. Springer, 2006. 177, 187

[21] Niyogi, S., and Adelson, E. Analyzing and recognizing walking figures in xyt. In *Computer Vision and Pattern Recognition, 1994. Proceedings CVPR '94., 1994 IEEE Computer Society Conference on* (June 1994), pp. 469 –474. 177

[22] Oeffinger, D., Brauch, B., Cranfill, S., Hisle, C., Wynn, C., Hicks, R., and Augsburger, S. Comparison of gait with and without shoes in children. *Gait & Posture 9*, 2 (1999), 95 – 100. Available from: `http://www.sciencedirect.com/science/article/B6T6Y-3WM59K1-2/2/3bb8b2c2146a23e175cc95434ec19de7`. 167, 178, 187

[23] Orr, R. J., and Abowd, G. D. The smart floor: a mechanism for natural user identification and tracking. In *CHI '00 extended abstracts on Human factors in computing systems* (New York, NY, USA, 2000), CHI '00, ACM, pp. 275–276. Available from: `http://doi.acm.org/10.1145/633292.633453`. 177, 187

[24] Pascoe, D., Pascoe, D., Wang, Y., Shim, D., and Kim, C. Influence of carrying book bags on gait cycle and posture of youths. In *Ergonomics* (1997), vol. 40, pp. 631–641. 167, 178

[25] Purwar, A., Jeong, D. D., and Chung, W. Y. Activity monitoring from real-time triaxial accelerometer data using sensor network. In *Control, Automation and Systems, 2007. ICCAS '07. International Conference on* (October 2007), pp. 2402 –2406. 178, 187

[26] Sutherland, D. H., Olshen, R. A., Biden, E. N., and Wyatt, M. P. *The development of mature walking*. Mac Keith Press, 1988. 178

[27] WANG, L., TAN, T., HU, W., AND NING, H. Automatic gait recognition based on statistical shape analysis. *Image Processing, IEEE Transactions on 12*, 9 (September 2003), 1120 – 1131. 177, 187

[28] YING, H., SILEX, C., SCHNITZER, A., LEONHARDT, S., AND SCHIEK, M. Automatic step detection in the accelerometer signal. In *Proceedings of the 4th International Workshop on Wearable and Implantable Body Sensor Networks (BSN 2007)* (2007). 167, 177

[29] YU, S., TAN, T., HUANG, K., JIA, K., AND WU, X. A study on gait-based gender classification. *Image Processing, IEEE Transactions on 18*, 8 (August 2009), 1905 –1910. 167, 177, 187

Appendix C

Gait Recognition in Children under Special Circumstances

Abstract

In this paper we investigate gait recognition in children's walking under special circumstances. Gait research so far has only focused on adult walking and mostly under normal walking conditions. This paper confirms that the results for adult walking under special circumstances also apply to children's walking.

In this paper we show that the performance of children's walking while carrying an object actually improves on the performance when walking normally, but when asked to walk fast the walking becomes unstable, resulting in a higher Equal Error Rate (EER). Furthermore we show that using a single template obtained from normal walking does not perform well when children can walk under various different circumstances.

C.1 Introduction

Gait analysis is defined as the study of human movement and has been the subject of considerable interest from researchers in the fields of bioengineering, physical therapy, neurology and rehabilitation for the management of medical problems affecting the locomotor system [22, 21, 23, 7, 26]. In addition, in recent years it has become important as a biometric feature in identification and recognition for the purposes of security and safety. Interest in gait spans several centuries dating back to descriptive studies by Leonardo di Vinci, Galileo and Newton with the first scientific description of gait being given by the Italian scientist Borelli in 1862 in "De Motu Animalum" [3]; he described human movement in terms of maintenance of the center of gravity by constant movement forward of the gait by the feet. Weber et al [24] gave a description of the gait cycle in 1836. Kinematic studies of gait began with Marcy in the 1870s culminating in more recent works by Bernstein in the 1930s using a variety of photographic techniques with over 150 subjects [19]. In the last couple of decades, there has been rapid development in technology such as electronics, sensors, photographic and video equipment and intelligent systems which has accelerated advances in gait analysis [12, 25, 16, 17].

Gait recognition has involved several approaches. The first is the machine vision based approach involving a video camera to analyze gait [23, 4]. The gait is captured from a distance with a video camera, and image processing techniques are used to extract gait data for recognition. Studies have shown that gait has distinctive patterns which can be used for individual recognition [5].

The second approach uses floor sensors, and the analysis of the movement on special surfaces gives information on gait recognition features [13, 18, 20]. A set of sensors is installed on the floor and gait related data is measured when subjects walk on these sensors and enables the collection of gait features such as ground reaction force, heel-to-toe ratio etc that are not readily captured with vision based systems.

The third and most recent approach involves wearing sensors on various areas of the body such as belt, leg, ankle and arm which measure acceleration along the x, y and z directions. The information extracted can be used to identify the gait cycle and salient features

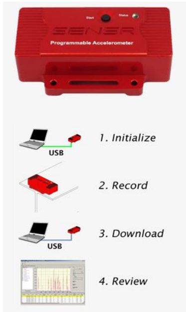


Figure C.1: GP 1 Sensor from Sensr, http://www.sensr.com.

of the human gait [10, 8, 6]. Various types of sensors are available such as accelerometers, gyro sensors, force sensors and bend sensors that measure a range of walking characteristics. They have been used for medical applications for patients with locomotion disorders. Such sensors are cheaper and readily available for gait analysis. However, very little work has been done on using wearable sensors in gait analysis for recognition. There are no reported studies of gait recognition in children.

This paper is a follow-up to our previous paper presented at [2] on gait recognition in children under normal walking conditions. Here we report on a study carried out with children walking under special circumstances such as carrying weighted objects and fast walking using the wearable accelerometer on the belt. The volunteers who participated in this study are the same children who participated in our previous study.

C.2 Experiment design and data analysis

In this study, a programmable sensor (Model GP1, see Figure C.1) purchased from Sensr (USA, `http://www.sensr.com`) was programmed and used to record the motion of the children in several walking cycles [14]. The GP1 measures the acceleration in three perpendicular directions that will be referred to as x, y and z. Figure C.2 shows an example of the output of the sensor. The GP1 can collect acceleration data between $\pm 2.5g$ to $\pm 10g$ and has a sampling rate of 100 Hz per axis. Acceleration data is filtered inside the GP1 by a 2 pole Butterworth low pass filter with a cut-off frequency of 45 Hz [1]. The device has a USB interface for transferring data and a 1 Mbyte memory for storage purposes.

C.2.1 Experiment design

This study involved the participation of 43 children (29 male and 14 female), with ages ranging from 5 to 16 years. The average male participant was 11.3 years old, while the female participants were on average 9.0 years old. Detailed information on the number of participants of a certain age is given in Table C.1. Approval was obtained from the school principal, the university's ethical approval committee and parents of the children. For each child the parents formally approved participation in the study by signing a standard University approved consent form prior to volunteering. The criteria set for the child to take part in this study were that they should have no previous history of lower extremity injury occurring within the past year, and no known musculoskeletal or neurological disease. Height and weight measurements were also taken. These measurements are not used however in the analysis presented in this paper.

In this experiment, the volunteers were asked to walk normally (to create a baseline performance) and in addition, walk under special circumstances. The special circumstances selected for this experiment were carrying an object and walking more quickly. The object that the volunteers were asked to carry was a 3.5 kg book. Due to their young age, two of

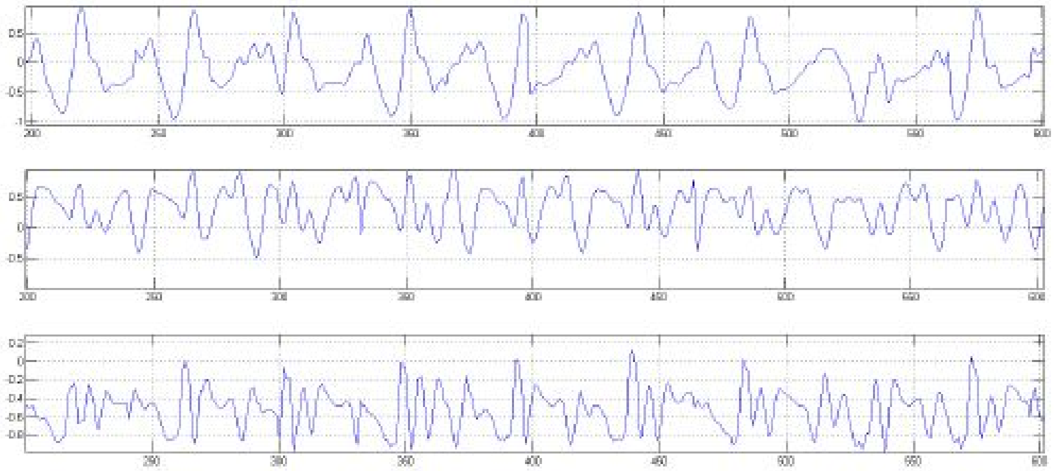


Figure C.2: Output example of the GP1 sensor.

Age	5	6	7	8	9	10
Number of Children	1	1	2	4	7	11
Age	11	12	13	14	15	16
Number of Children	4	3	2	4	1	3

Table C.1: Age distribution of participants.

the participants were not able to carry that book and instead carried a lighter book. The ages of these participants were 5 and 7 year and the other book they carried weight 1.5 kg. For the fast walking, the children were instructed to walk at a higher speed than what they consider to be a normal walking speed but to not run.

The GP1 sensor was attached to a belt and positioned on the left hand side of the hip. Volunteers were asked to walk for a distance of approximately 17.5 meters in a carpeted hall on a flat surface without shoes. At the end of the hall the volunteers waited 5 seconds, turned round, waited a further 5 seconds and then walked back. They repeated this procedure four times after which the sensor was detached from the volunteer and connected to the PC for downloading the data. The recorded data was stored on a PC for later analysis and file naming was done later to recognize the participant and the type of walking from the filename.

The walking procedure was repeated 4 times in total. Depending on the age of the child, either 2 sessions were carried out on one day and two on another, or all 4 sessions were carried out on a single day. In the first two of these sessions the participants walked at their normal speed, while the third session was for faster walking test, and the last session was used for the walk whilst carrying the object. On each occasion the volunteers walked the full length of the hallway $4 \times 2 = 8$ times. This implies that in total they walked the hallway 16 times at normal speed, 8 times at a higher speed, and 8 times carrying the object. In the remainder of this paper, we will refer to a *walk* as the data collected from walking the full length of the hallway once. In other words, the data of each participant represents $16 + 8 + 8 = 32$ walks.

The gait samples for normal walking have been analyzed in [2] and the optimal result was a 12.7% Equal Error Rate (EER). The purpose of this research is to look at performance degradation when the children are not walking in their normal way, but when special circumstances apply.

C.2.2 Data preprocessing and analysis

As described, each participant walked in four different sessions and each session was downloaded as a separate file to the PC. Each of these files contained the data of 8 assessed walks, each again separated by standing still, turning and again standing still. In each file the data representing a walk could be differentiated from standing still by looking at the variation in the data over a 50 sample period (representing 0.5 seconds). The turning could also be removed from the relevant walking data, not by looking at the variation in the data but at the duration of the activity; while turning took only a brief moment, a full walk of the hall took at least 10 seconds (i.e. at least 1000 samples). The data from each collected file was thus split into 8 separate files, where each file contained a single separated walk of the hall.

Using the above method the originally $43 \times 4 = 172$ collected files were split into $172 \times 8 = 1376$ files, where each file contained the data of exactly one walk. Each file was labeled in such a way that participant, session number (1 or 2), walk within session (1..8), and type of walk (normal, carrying, or fast) were identifiable from the filename. Each file contained 4 columns, representing respectively the time, the x-acceleration, the y-acceleration and the z-acceleration. The values in the time column were the original values from the collected files. The time value increased by 0.01 from one row to the next because the sampling rate was 100 samples per second.

Each of the files containing the data of a single walk was processed next using the Average Cycle Method (ACM). The ACM (see [6] for details) has been applied to the collected data. In our analysis in step 1 of the ACM, the noise was reduced by using the Weighted Moving Average (WMA) filter of length 5 and weights $(\frac{1}{9}, \frac{2}{9}, \frac{3}{9}, \frac{2}{9}, \frac{1}{9})$ on the data of each of the three separate directions. The three directions were then combined to a single value by calculating the resultant acceleration: $r_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$. The detection of cycles in step 2 of the ACM was done using the Salience method from [15]. As the best performance in [2] was reached by not creating an average cycle, but by keeping all detected cycles, we have now applied that method here too, i.e. we followed the work of Gafurov et al. [9]. Again, because it resulted in the best performance when analyzing the data in [2], we decided to use the Dynamic Time Warping distance metric in combination with the rotation method as described in [8].

We performed various analyses. From [2] we already know that the performance of normal walking for children has an EER of 12.7%. The first tests we applied were to check how well children could be recognized when comparing a template from either carrying or walking fast against a test data sample from the same set. In these two cases, the first of the 8 data samples for a circumstance is used to create a template and the remaining 7 are used as test inputs for the performance evaluation. We applied two more tests to see the difference between fast walking or walking when carrying an object, and normal walking. In this case templates from normal walking were used and tested against 8 test inputs from fast walking or 8 test inputs from walking while carrying an object. Results of the tests are presented in Section C.3.

C.3 Results

In this section we will present the results of the analysis. The results from performing the analysis as described in section C.2.2 are presented in Table C.2. The first and second columns in this table represent the type of gait data used for creating the template, and the type of data used for test input. The third and fourth columns represent the number of genuine and impostor scores used in this analysis. Furthermore the fifth column represents the EER for that particular test and the last column represents the performance degradation from the normal walking situation. Performance degradation is calculated as the difference between EER of a particular test and the EER for the baseline situation, divided by the EER of the baseline situation. The baseline situation is where both template and test input

Template	Test Input	# of Gen. Scores	# of Imp. Scores	EER	Degradation
Normal	Normal	645	27090	12.7%	0%
Normal	Carrying	344	14448	25.4%	100%
Normal	Fast	344	14448	33.4%	163%
Normal	Fast & Carrying	688	28896	35.9%	183%
Fast	Fast	301	12642	22.2%	75%
Carrying	Carrying	301	12642	10.1%	-20%

Table C.2: Performance results on the collected dataset.

are based on normal walking and the EER in that case is 12.7%. In all cases the analysis method to calculate the EER has been a combination of using separate cycles from [9] in combination with the rotation method from [8].

From this table several conclusions can be made. First of all, walking faster results in a less stable gait and because of that a higher EER value. The performance degradation from normal to fast walking is 75% and when compare to a normal walking template, then the performance degradation is even greater (163%). This phenomena, that fast walking is less stable than normal walking, has been observed before in [11]. There it can be seen that the performance degradation from normal to fast walking is 80%, which is in accordance with our results.

We can also see there is a performance improvement when children are carrying an object. Although this result seems odd at first glance, there is a rational explanation. The children were instructed to walk in a normal manner and anyone given that instruction will up to a certain degree start to think about the way they walk. This will then result in slight deviations from the actual way of normal walking and will result in a slightly unstable gait. When the children were asked to carry a 3.5 kg book, their minds was taken off the task of walking normally, which then actually resulted in them walking in a natural and more stable way [14]. More research should confirm that the given explanation is indeed correct.

We have also tested the situation where the template represented normal walking and the test input was from either fast walking, or walking while carrying an object or both. This represents a scenario where a normal walking template is applied but a child's current way of walking deviates from that. We see that in all cases we have a severe performance degradation, where the degradation for walking when carrying an object is the least. These results show that walking carrying an object or walking fast are really different from walking normally. Children can to some degree still be recognized, but the high EER clearly shows that we cannot use a single template (for normal walking) to recognize a person under all circumstances.

C.4 Conclusions

In this paper we presented the results of gait recognition in young children when walking under special circumstances. We can conclude that a single template for normal walking will not be sufficient to recognize the children walking fast or carrying an object. The performance of gait recognition improves especially when carrying an object, which might be due to the fact that the participants in the experiment were no longer focusing on the way they walked. Fast walking had been known to be less stable than normal walking and these results have been confirmed in this study. The results for the gait studies on children agree with those of the previous study carried out with adults when considering the performance degradation from normal walking to fast walking (80% for adults and 75% for children).

Future research should focus also on different walking circumstances like walking slow, or walking up or down stairs. It would be interesting to see the influence of the particular object that is carried on the walking stability. Carrying a 3.5 kg book is clearly different from carrying a glass of water, and the difference is not only due to the weight of the object. More research is needed to confirm that the increased performance when walking while carrying an object is due to the distraction from the actual walking.

C.5 Acknowledgments

The authors would like to thank all the (anonymous) children and their parents that participated in this experiment. The writing of this article would not have been possible without their effort in the data collection phase.

C.6 Bibliography

[1] Gp1 programmable accelerometer user manual. www.sensr.com, 2007. 168, 178, 188

[2] BALISANE, H., DERAWI, M., BOURS, P., WAQAR, A., AND TWIGG, P. Performance of gait recognition in children's walking compared to adults. In *Security and Communication Networks (IWSCN), 2011 3rd International Workshop on* (2011). 167, 188, 189, 190

[3] BORELLI, G.-A., AND BERNOUILLII, J. *De Motu Animalium*. Kessinger Publishing, 2009. 177, 187

[4] BOUCHRIKA, I., AND NIXON, M. Exploratory factor analysis of gait recognition. In *Automatic Face Gesture Recognition, 2008. FG '08. 8th IEEE International Conference on* (September 2008), pp. 1 –6. 167, 187

[5] BOUCHRIKA, I., AND NIXON, M. S. Model-based feature extraction for gait analysis and recognition. In *Proceedings of the 3rd international conference on Computer vision/computer graphics collaboration techniques* (Berlin, Heidelberg, 2007), MIRAGE'07, Springer-Verlag, pp. 150–160. Available from: `http://portal.acm.org/citation.cfm?id=1759437.1759452`. 187

[6] BOURS, P., AND SHRESTHA, R. Eigensteps: A giant leap for gait recognition. In *Security and Communication Networks (IWSCN), 2010 2nd International Workshop on* (May 2010), pp. 1 –6. 167, 178, 180, 181, 188, 190

[7] DEGEN, T., JAECKEL, H., RUFER, M., AND WYSS, S. Speedy:a fall detector in a wrist watch. In *Wearable Computers, 2003. Proceedings. Seventh IEEE International Symposium on* (October 2003), pp. 184 – 187. 178, 187

[8] DERAWI, M., BOURS, P., AND HOLIEN, K. Improved cycle detection for accelerometer based gait authentication. In *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference on* (October 2010), pp. 312 –317. xi, 167, 170, 171, 172, 178, 181, 182, 188, 190, 191

[9] GAFUROV, D., SNEKKENES, E., AND BOURS, P. Improved gait recognition performance using cycle matching. In *Advanced Information Networking and Applications Workshops (WAINA), 2010 IEEE 24th International Conference on* (April 2010), pp. 836 –841. 181, 182, 190, 191

[10] GAFUROV, D., SNEKKENES, E., AND BUVARP, T. E. Robustness of biometric gait authentication against impersonation attack. In *OTM Workshops (1)* (2006), R. Meersman, Z. Tari, and P. Herrero, Eds., vol. 4277 of *Lecture Notes in Computer Science*, Springer, pp. 479–488. 167, 177, 188

[11] HOLIEN, K. Gait recognition under non-standard circumstances. Master's thesis, Gjøvik University College (HIG), June 2008. 191

[12] KALE, A., SUNDARESAN, A., RAJAGOPALAN, A., CUNTOOR, N., ROY-CHOWDHURY, A., KRUGER, V., AND CHELLAPPA, R. Identification of humans using gait. *Image Processing, IEEE Transactions on 13*, 9 (September 2004), 1163 –1173. 177, 187

[13] MIDDLETON, L., BUSS, A., BAZIN, A., AND NIXON, M. A floor sensor system for gait recognition. In *Automatic Identification Advanced Technologies, 2005. Fourth IEEE Workshop on* (October 2005), pp. 171 – 176. 177, 187

[14] MJAALAND, B., BOURS, P., AND GLIGOROSKI, D. Walk the walk: Attacking gait biometrics by imitation. In *Information Security*, M. Burmester, G. Tsudik, S. Magliveras, and I. Ilic, Eds., vol. 6531 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, 2011, pp. 361–380. Available from: `http://dx.doi.org/10.1007/978-3-642-18178-8_31`. 191

[15] NICKEL, C., DERAWI, M. O., BUSCH, C., AND BOURS, P. Field test of accelerometer-based biometric gait recognition. In *3rd International Workshop on Security and Communication Networks (IWSCN)* (2011). 180, 190

[16] NIXON, M. S., TAN, T. N., AND CHELLAPPA, R. *Human Identification Based on Gait*. Springer, 2006. 177, 187

[17] OEFFINGER, D., BRAUCH, B., CRANFILL, S., HISLE, C., WYNN, C., HICKS, R., AND AUGSBURGER, S. Comparison of gait with and without shoes in children. *Gait & Posture 9*, 2 (1999), 95 – 100. Available from: `http://www.sciencedirect.com/science/article/B6T6Y-3WM59K1-2/2/3bb8b2c2146a23e175cc95434ec19de7`. 167, 178, 187

[18] ORR, R. J., AND ABOWD, G. D. The smart floor: a mechanism for natural user identification and tracking. In *CHI '00 extended abstracts on Human factors in computing systems* (New York, NY, USA, 2000), CHI '00, ACM, pp. 275–276. Available from: `http://doi.acm.org/10.1145/633292.633453`. 177, 187

[19] PITKIN, M. R. *Biomechanics of Lower Limb Prosthetics*. Springer, 2009. 167, 187

[20] PURWAR, A., JEONG, D. D., AND CHUNG, W. Y. Activity monitoring from real-time triaxial accelerometer data using sensor network. In *Control, Automation and Systems, 2007. ICCAS '07. International Conference on* (October 2007), pp. 2402 –2406. 178, 187

[21] TANAWONGSUWAN, R., AND BOBICK, A. Performance analysis of time-distance gait parameters under different speeds. In *Audio- and Video-Based Biometric Person Authentication*, J. Kittler and M. Nixon, Eds., vol. 2688 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, 2003, pp. 1060–1060. Available from: `http://dx.doi.org/10.1007/3-540-44887-X_83`. 187

[22] TANAWONGSUWAN, R., AND BOBICK, A. Modelling the effects of walking speed on appearance-based gait recognition. In *Computer Vision and Pattern Recognition, 2004. CVPR 2004. Proceedings of the 2004 IEEE Computer Society Conference on* (June 2004), vol. 2, pp. II–783 – II–790 Vol.2. 187

[23] WANG, L., TAN, T., HU, W., AND NING, H. Automatic gait recognition based on statistical shape analysis. *Image Processing, IEEE Transactions on 12*, 9 (September 2003), 1120 – 1131. 177, 187

[24] WHITTLE, M. W. *Gait Analysis: An Introduction*, 4 ed. Butterworth-Heinemann, 2007. 187

[25] YAM, C., NIXON, M., AND CARTER, J. On the relationship of human walking and running: automatic person identification by gait. In *Pattern Recognition, 2002. Proceedings. 16th International Conference on* (2002), vol. 1, pp. 287 – 290 vol.1. 187

[26] YU, S., TAN, T., HUANG, K., JIA, K., AND WU, X. A study on gait-based gender classification. *Image Processing, IEEE Transactions on 18*, 8 (August 2009), 1905 –1910. 167, 177, 187

Appendix D

Gait Recognition using Time-of-Flight Sensor

Abstract

This paper develops a biometric gait recognition system based on 3D video acquired by a Time-of-Flight (ToF) sensor providing depth and intensity frames. A first step of the proposed gait analysis is the automatic extraction of the silhouette of the person via segmentation. The segmentation of the silhouette is performed on the depth frame which provide information which describes the distance from the camera of every pixel in the intensity frame. The range data is sensitive to noise thus we apply morphological filtering operations to enhance the segmented object and eliminate the background noise. The positions of the joint angles are estimated based on the splitting of the silhouette into several body segments, based on anatomical knowledge, and ellipse fitting. The resulting parameters from this analysis of the silhouette are used for feature extraction from each frame. The evolutions of these features in time are used to characterize the gait patterns of the test subjects. Finally, we do biometric performance evaluation for the whole system. To the best of our knowledge, this article is the first article that introduces biometric gait recognition based on ToF Sensor.

D.1 Introduction

The ability to use gait for people recognition and identification has been known for a long time. The earliest research started in the sixties of the twentieth century, where studies from medicine [14] and psychology [10] proved that human gait has discriminative patterns from which individuals can be identified. It is however just in the last decade that gait as a biometric feature has been introduced, and from a technical point of view gait recognition can be grouped in three different classes. Machine vision (MV) which uses video from one or more cameras, to capture gait data and video/image processing to extract its features. Floor sensors (FS), that use sensors installed in the floor, are able to measure gait features such as ground reaction forces and heel-to-toe ratio when a person walks on them. The third class uses wearable sensors (WS) where the gait data is collected using body-worn sensors.

MV based gait recognition is mainly used in surveillance and forensics applications [12, 8]. In MV image processing techniques are used to extract static like stride length which are determined by body geometry [2], and dynamic features from body silhouettes. The MV based gait analysis techniques can be classified as model-based [3] and model free [7]. The main advantage of model based approaches is the direct extraction of gait signatures from model parameters, but it is computationally expensive. Model free techniques characterize the body motion independently from body structure. MV gait analysis can also be categorized according to the technology used, as marker-based or marker-less. In marker based systems specific points in the subject's body are labeled by markers. By tracking these points in the video sequence the body motion can be tracked and analyzed [4, 11]. MV based gait recognition provides wide range of gait features and many works utilized different sets of features and classification techniques. Benabdelkader et. al. [1] used stride length and cadence as features extracted from 17 subjects' silhouettes walking in outdoor environment for 30 meters in a straight line at fixed speed to achieve EER of 11%, using linear regression for classification. Wang et. al. [17] utilized silhouette structure evolution over time to characterize gait, by calculating the silhouette centre and obtaining its contour they converted the 2D silhouette into 1D signal by calculating the distance between the centroid and every pixel on the contour. Principal component analysis (PCA) were used for dimensionality reduction of normalized distance signals using normalized Euclidean distance (NED) as similarity measure and nearest neighbour classifier with respect to class exemplars (ENN) classification approach. They achieved an EER of 20%, 13%, and 9% for 20 subjects filmed at 0, 45, and 90 degrees view respectively. The most related work to ours was done by He and Le [7], in which temporal leg angles was used as gait features for 4 walking styles slow, fast, incline and walking with a ball, on a running machine. They achieved wide range of CCR for the different walk styles using NN and ENN classification techniques. The best result for 9 subjects were in worst case 74,91% using NN for the shin parameters alone in fast walk and best case 100% using NN for merging thigh the shin parameters alone in ball walk, running the test over the whole CMU database 96.39 % was achieved for fast walk. Jensen et. al [9] used ToF camera to analyse gait, in their work step and stride length, speead, cadence and angles of joints were extracted as extracted as gait features. They used model fitting technique to extract the joint angles. To the best of our knowledge, this article is the first article that introduces biometric gait recognition with the use of ToF Sensor.

D.2 Experiment Design

In order to verify the usefulness of the proposed system, we performed an individual gait identification experiment. In this section we will go through the different issues related to our experiment.

We used the Swiss ranger SR-4000 CW10 sensor by Mesa technologies [13] seen in Figure D.1. The SR4000 is an optical imaging system housed in an anodized aluminum enclosure. The camera operates with 24 LED emitting infra-red in the 850nm range, it modulates the illumination light emitting diodes (LED) at modulation frequency of 15MHz. Range measurements are obtained at each pixel using the phase shift principle, with non-ambiguity range of 10 meters. The camera has USB port for data acquisition and supplied with software library for C and Matlab.

Figure D.1: SR-4000 ToF sensor

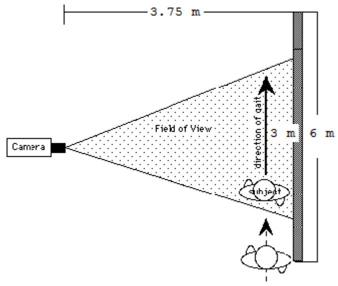


Figure D.2: set-up of the experiment

The subject's motion was filmed from the side by means of a ToF camera at 30 frames/sec, while the subject was walking on a track in front of the camera as shown in Figure D.2. Due to the camera's narrow field of view, the length of the filmable track was limited to about 3 meters, therefore the subjects were asked to walk back and forth 10 times on a track longer than the camera's field of view's width. we used this longer track to allow recording the subject in full motion. To reduce the noise in the distance data, the camera was calibrated such that the image starts from the walking track in order to eliminate the reflection from the floor. The camera was put on a tripod at 0.7 meter from the floor and was tilted up about 5 degrees, as recommended by the camera manufacturer, see Figure D.2.

The experiment was carried out on a solid surface in the lab. The subjects were asked to walk a fixed track in front of the camera. This fixed track allow the participants to walk for 1.5 to 2 gait cycles depending on the participants gait characteristics, and because some of the participants may not start precisely at the marker where the field of view of the camera starts. Each participant walks the track at least 5 times to extract one full gait cycle from each pass in front of the camera. The experiment procedure by the participant can be summarized in three steps to be repeated 5 times on average. First, the user *walks the track*, *turns around* and *walks the track back*.

The experiment was done in lab at Gjøvik University College. An invitation was sent to the students at the faculty to participate in the experiment, and 30 participants volunteered. They were of different age and height groups. The average age for the volunteers was 29.1 years, the average height was 176.9 cm. The participants were asked to wear the same type of shoes during the two sessions. In the experiment two sessions we collected data for the 30 subjects over a month, time gap between the two session varied from subject to subject, for a few subjects it was one week and for others about a month.

D.3 Feature Extraction

The image sequences of the subjects were acquired while walking in front of the camera. Followed by segmentation to extract the subjects body silhouette, morphological operations are applied to reduce background noise and fill holes in the extracted human silhouettes. Next, each of the enhanced human silhouettes is divided into six body segments based on human anatomical knowledge [15]. Ellipse fitting is applied to each of the six segments, and the orientation of each of the ellipses is used to calculate the orientation of each of the lower body parts for further analysis. The following steps are hereby described in more details:

Video segmentation is the process of partitioning a video spatially or temporally. It is an integral part of many video analysis and coding systems, including video indexing and retrieval, video coding, motion analysis and surveillance. In order to perform gait analysis of a person from image sequence, the subject needs to be extracted from the background of the video sequence. Image segmentation is used to separate foreground objects like people, from the background of the image sequence. Thresholding is the simplest image segmentation technique, in which each pixel of the original image is compared to a specified threshold, if the pixel's value is greater than the threshold value it is set as foreground pixel with value 1 if not it is set to zero as background pixel producing a binary image. In some complex images the operation can be iterated using two thresholds, in this case threshold works like band pass filtering. Histograms can be used to find the proper threshold values [16], where peaks correspond to foreground objects are used to determine the threshold values. If the image's histogram shows no clear peaks, then, thresholding can not produce acceptable segmentation.

Morphological operations are shape based technique for processing of digital images [6]. Morphological operations are used to simplify image data preserving their main shape characteristics and eliminating irrelevant details. Morphological operations have two inputs the original image and structuring element to be applied to the input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. The shape and size of the structuring element constructs a morphological operation that is sensitive to specific shapes in the input image. The most basic morphological operations are dilation and erosion.

Ellipse fitting is used next to find the characteristics of the body parts. Having extracted body silhouette, the subject body are segmented into six parts [15] as illustrated in Figure

D.3. First, the centroid of the silhouette is determined by calculating its center of mass. The area above the centroid is considered to be made of the upper body, head, neck and torso. The area below the centroid is considered made of the lower body, legs and feet. Next, one third of the upper body is divided into the head and neck. The remaining two thirds of the upper body are classified as the torso. The lower body is divided into two portions thighs and shins. Fitting an ellipse to each of the six body parts and finding their centres of mass, orientations, and major axes length we can characterize these body parts. Evolution of these parameters in the video sequence describes the human gait characteristics in time.

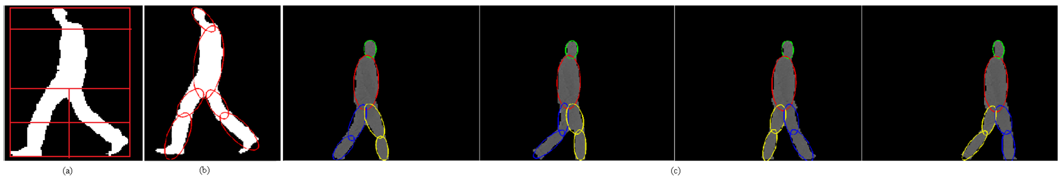


Figure D.3: *(a)*: body parts, *(b)*: ellipse fitting model and *(c)* tracking of legs, blue ellipses for the leg closer to the camera

Leg tracking is performed next. Gait analysis requires reliable tracking of moving human body segments. As the human body is segmented into six parts, we need to track the lower limbs in the successive frames to construct meaningful output of the measured angles in the following step. To track the body parts along the image sequence we utilize the depth information acquired at each frame, we calculate the mean range values of each segment. The segment with higher mean range value belongs to the farthest away leg from the camera and vice versa, in Figure D.3(c) a sample sequence of images with tracking results are shown.

Leg angles calculation is the last step of the features extraction. Human body is modeled as rigid segments connected by joints. The simplest model as 2D stick [5], as in Figure (D.4-a). To extract the gait signatures we will mainly extract the thigh and shin angles from each frame of the video sequence to characterize the gait cycle. In this final step we extract the angles based on the data extracted from ellipse fitting to the body segments. The fitted ellipse parameters: orientation, major axis length (l_{major}) and centroid will be used to approximately calculate the start and end points coordinates for each of the body segments, such that each segment will be defined by two points in two dimensional space ((p_{i1}, p_{i2})) using equations ($x_1 = x_0 + l_{major} * cos(\varphi)$), ($x_2 = x_0 - l_{major} * cos(\varphi)$), ($y_1 = y_0 + l_{major} * sin(\varphi)$) and $y_2 = y_0 - l_{major} * sin(\varphi)$ as shown in Figure (D.4-b). To

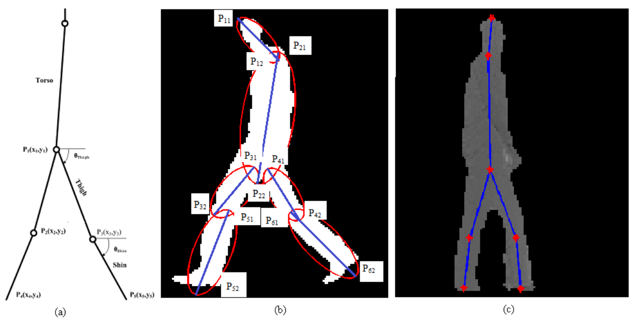


Figure D.4: Illustration of joint locations, (a) 2D stick figure, (b) sample frame and (c) calculated angles.

calculate the angles of the leg segments, we reduced the impact of the non-precise fitting of the ellipses to the body segments, by estimating the location of the joints as the average location of the start point of one of the segments and the end point of the segment connected by the joint. The hip and knee joints' locations are calculated by the equation set ($p_1 = \frac{p_{22}+p_{31}+p_{41}}{3}$), ($p_2 = \frac{p_{32}+p_{51}}{2}$) and $p_3 = \frac{p_{42}+p_{61}}{2}$ as shown in Figure D.4(c) The extracted features for each of the segments were calculated by equation $\theta = arctan\frac{y_2-y_1}{x_2-x_1}$. We calculate the inclination angle of thigh and shin for each of the subject's legs to characterize the gait by the evolution of these angles in time at each image of the video sequence. Since the gait is quasi-periodic movement we extract a single gait cycle from each video sequence. The extracted feature are filtered using a local median filter to filter out the outliers. The outliers can be due to losing track of the legs, or bad ellipse fitting, in Figure D.5 plots for 5 different gait cycle for one subject before and after filtering.

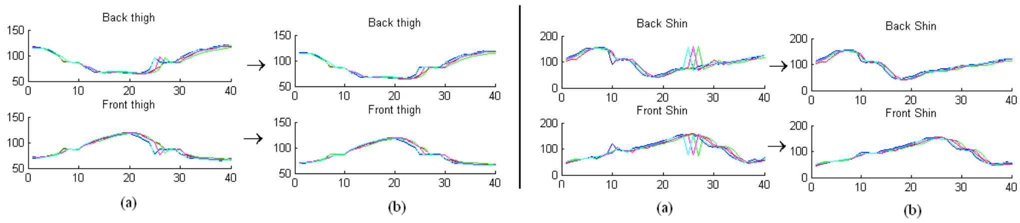


Figure D.5: Extracted data for 5 different walking cycles,(a): original data, (b):filtered data.

D.4 Analysis and Results

As mentioned in earlier sections, each participant was filmed during two different sessions, and each session was downloaded as a separate file to the PC. Each of these files contained the data of 5 assessed gait data records, each again separated by leg types, i.e. front shin, back shin, front thigh and back thigh. In each file the data representing more than one gait cycle was manually aligned and cut such that one cycle started at a minimum and ended at a minimum value. This was done for all files. So the data from each collected file was split into 4 other files (for each leg type).

Using the above method the originally 30 $\times$ 5 = 150 collected files were split into 150 $\times$ 4 = 600 files, where each file contained the data of exactly one gait cycle for each leg type. Each file was labeled in such a way that participant, session number (1 or 2) and type of leg (front shin, back shin, front thigh, back thigh) are identifiable from the file name. Each file contained one column, representing the feature vector. The length of this feature vector varied indicating the length of gait cycle was varying from one participant to another. For the second session, 20 out of the 30 volunteers participated. This means that the performance evaluation over a certain time interval will only consist with 20 volunteers.

In our analysis in step 1, the noise was reduced by using the running median filter as described in the previous section. This resulted in having a filtered gait cycle representing our new feature vector. Since each file has dissimilar lengths we were unable to use distance metrics such as the Manhattan or Euclidean. Instead we applied a time series analysis named the Dynamic Time Warping (DTW) which is an algorithm for measuring similarity between two sequences which may vary in time or speed.

Several performance evaluations were calculated. Table D.1 shows the performance of the first session with 30 subjects (second column) and the subset of 20 users (third column) who also participated at the second session. The first column indicates which template and test input were applied for performance testing. We notice that if we apply all the four types of legs as feature vector for one subject, we obtain an better EER than when applying them separately. This is due to the fact that more information is stored for a given subject. Since only a subset of users participated at the second session the EER has not changed significantly. With the performances for the second session we observe a significant change of the performance and the reason is that the users are more used to the walking in the second session and more comfortable with the experiment.

Template/Test	30 Participants	20 Participants - 1st	20 Participants - 2nd
Back thigh	8.42	7.48	4.72
Front thigh	7.39	6.62	6.02
Back shin	12.31	11.16	6.28
Front shin	11.32	10.24	9.41
All above	4.63	4.08	2.62

Table D.1: EER Performance Results in % on the collected dataset. Second column is first session. Last column is session session

An interesting performance analysis is to investigate the change between the two session as can be seen in Table D.2. We are analysing what will happen if we apply the first sessions data as training set and the second sessions data as test input. What we observe here is that the change over time becomes worse. Different shoe-type, clothes may have also an impact, and we realized that unfortunately not all participants came back for the second session.

Session 1	Session 2	Session 1 + Session 2
4.09	2.48	9.25

Table D.2: EER Performance Results in % where session 1 as reference template and session 2 as test input (20 users).

D.5 Conclusion

In this paper we presented the first known results on gait recognition using the 3D ToF Sensor. When analyzing the data we could already visually see that gait cycles were detectable for each subject which are dissimilar from others'. The experiment was performed over two different days (sessions) where each of the subjects (first session 30 subjects, second session 20 subjects) walked a track within the camera field of view. The best equal error rate obtained was 2.66 % for a separate session where the change over time we retrieve an equal error rate of about 9.25 %. Although the last mentioned result is not so low, this paper presents a first step towards a better performance in the future. Future work includes to work with multiple session over multiple days, and more cycles person to see the stability over time.

D.6 Acknowledgments

The authors would like to thank all the (anonymous) participants in this experiment. The writing of this article would not have been possible without their effort in the data collection phase.

D.7 Bibliography

[1] BENABDELKADER, C., CUTLER, R., AND DAVIS, L. Stride and cadence as a biometric in automatic person identification and verification. In *FG'02* (2002), pp. 372–377. 18, 195

[2] BOBICK, A. F., AND JOHNSON, A. Y. Gait recognition using static, activity-specific parameters. In *CVPR 2001* (2001), vol. 1. 18, 195

[3] BOUCHRIKA, I., AND NIXON, M. S. Model-based feature extraction for gait analysis and recognition. In *Mirage: Computer Vision ? Computer Graphics Collaboration Techniques and Applications* (March 2007), vol. 4418, pp. 150–160. 18, 195

[4] CUTTING, J., . K. L. Recognizing friends by their walk: Gait perception without familiarity cues. *Bull. Psychon. Soc. Vol. 9* (1977), pp. 353–356. 18, 195

[5] GUO, Y., XU, G., AND TSUJI, S. Tracking human body motion based on a stick figure model. 1–9. 198

[6] HARALICK, R. M., STERNBERG, S. R., AND ZHUANG, X. Image analysis using mathematical morphology. *IEEE PAMI 9*, 4 (july 1987), 532 –550. 197

[7] HE, W., AND LI, P. Gait recognition using the temporal information of leg angles. In *ICCSIT 2010* (2010), vol. 5, pp. 78 –83. 195, 196

[8] HU, W., TAN, T., WANG, L., AND MAYBANK, S. A survey on visual surveillance of object motion and behaviors. *IEEE–J–SMCC 34*, 3 (2004), 334–352. 17, 195

[9] JENSEN, R., PAULSEN, R., AND LARSEN, R. Analyzing gait using a time-of-flight camera. In *Image Analysis*, vol. 5575 of *LNCS*. Springer Berlin / Heidelberg, 2009, pp. 21–30. Available from: `http://dx.doi.org/10.1007/978-3-642-02230-2_3`. 196

[10] JOHANSSON, G. Visual perception of biological motion and a model for its analysis. *Perception & Psychophysics 14* (1973), 201–211. 195

[11] KUMAR NEELESH, KUNJU NISSAN, K. A. S. B. S. Active marker based kinematic and spatio-temporal gait measurement system using labview vision. *JSIR Vol.69(08)* (2010), 600–605. 18, 195

[12] LARSEN, P. K., SIMONSEN, E. B., AND LYNNERUP, N. Gait analysis in forensic medicine. *Journal of Forensic Sciences 53*, 5 (2008), 1149–1153. 17, 195

[13] MESA. http://www.mesa-imaging.ch/. 196

[14] MURAI, A., YAMANE, K., AND NAKAMURA, Y. Characterization of motor skill based on musculoskeletal model. In *EMBC 2009* (2009), pp. 6542–6545. 195

[15] NG, H., TAN, W.-H., TONG, H.-L., ABDULLAH, J., AND KOMIYA, R. Extraction and classification of human gait features. In *Visual Informatics: Bridging Research and Practice*, vol. 5857 of *LNCS*. Springer Berlin-eidelberg, 2009, pp. 596–606. 197

[16] OTSU, N. A threshold selection method from gray-level histograms. *Systems, Man and Cybernetics, IEEE Transactions on 9*, 1 (jan. 1979), 62 –66. 197

[17] WANG, L., TAN, T., NING, H., AND HU, W. Silhouette analysis-based gait recognition for human identification. 1505–1518. 195

Appendix E

Fingerprint Recognition with Embedded Cameras on Mobile Phones

Abstract

Mobile phones with a camera function are capable of capturing image and processing tasks. Fingerprint recognition has been used in many different applications where high security is required. A first step towards a novel biometric authentication approach applying cell phone cameras capturing fingerprint images as biometric traits is proposed. The proposed method is evaluated using 1320 fingerprint images from each embedded capturing device. Fingerprints are collected by a Nokia N95 and a HTC Desire. The overall results of this approach show a biometric performance with an Equal Error Rate (EER) of 4.5% by applying a commercial extractor/comparator and without any preproccesing on the images.

E.1 Introduction

Current mobile devices implement various new kinds of applications such as taking photos, and movie shooting by using embedded camera devices. This progress was made possible by the evolution of miniaturized embedded camera technology. Mobile devices – particularly mobile phones – are being found in almost everyone's hip pocket these days all over the world. Almost all newer cell phones now-a-days have embedded camera devices, and some of those have more than over 5 mega-pixel image cameras.

From a security point of view, the issues related to ever-present mobile devices are becoming critical, since the stored information in them (names, addresses, messages, pictures and future plans stored in a user calendar) has a significant personal value. Moreover, the services which can be accessed via mobile devices (e.g., m-banking and m-commerce, e-mails etc.) represent a major value. Therefore, the danger of a mobile device ending up in the wrong hands presents a serious threat to information security and user privacy. According to the latest research from Halifax Home Insurance claims, 390 million British pounds a year is lost in Britain due to the theft of mobile phones. With the average handset costing more than 100 British pounds, it is perhaps not surprising that there are more than 2 million stolen in the UK every year [9].

Authentication is an area which has grown over the last decades, and will continue to grow in the future. It is used in many places today and being authenticated has become a daily habit for most people. Examples of this are PIN code to your banking card, password to get access to a computer and passport used at border control. We identify friends and family by their face, voice, how they walk, etc. As we realize there are different ways in which a user can be authenticated, but all these methods can be categorized into one of three classes [20]. The first is *something you know* (e.g., a password), the second is *something you have* (e.g., a token) and the third is *something you are* (e.g., a biometric property).

Unlike passwords, PINs, tokens etc. biometric characteristics cannot be stolen or forgotten. The use of biometric was first known in the 14th century in China where ”Chinese merchants were stamping childrens palm- and foot prints on paper with ink in order to distinguish young children from one another”. Approximately after 500 years has passed, the first fingerprinting was used for identification of persons. In 1892, the Argentineans developed an identification system when a woman was found guilty of a murder after the investigation police proved that the blood of the womans finger on the crime scene was hers. The main advantage of biometric authentication is that it establishes an explicit link to the identity because biometrics use human *biological* and *behavioral* characteristics. The first mentioned are the biometrics derived directly from the part of a human body. The most used and prominent examples are the fingerprint, face, iris and hand recognition. The behavioral characteristics are the biometrics by persons behavioral characteristics, such as gait-recognition, keystroke recognition, speech/voice recognition and etc.

Many fingerprint recognition algorithms perform well on databases that had been collected with high-resolution cameras and in highly controlled situations [10]. Recent publications show that the performance of a baseline system deteriorates from Equal Error Rate (EER) around 0.02 % with very high quality images to EER = 25 % due to low qualities images [15]. Thus active research is still going on to improve the recognition performance. In applications such as fingerprint authentication using cameras in cell phones and PDAs, the cameras may introduce image distortions (e.g., because of fish-eye lenses), and fingerprint images may exhibit a wide range of

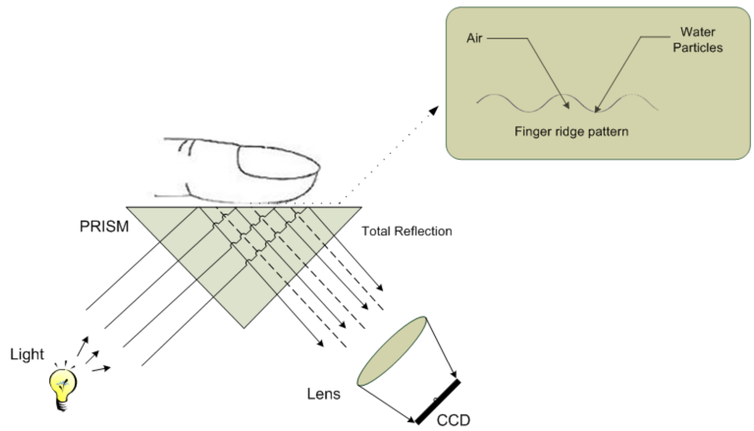


Figure E.1: Optical fingerprint sensing by frustrated total internal reflection.

illumination conditions, as well as scale and pose variations. An important question is which of the fingerprint authentication algorithms will work well with fingerprint images produced by cell phone cameras?

However, recent research [18, 16] have shown that by using low-cost webcam devices it is possible to extract fingerprint information when applying different pre-processing and image enhancements approaches. In this paper we present fingerprint recognition as means of verifying the identity of the user of a mobile phone. The main purpose of this paper is to study how it is possible to lower down the user effort while keeping the error rates in an acceptable and practical range. Therefore, this proposal is a realistic approach to be implemented in mobile devices for user authentication. To address this issue, we collected a fingerprint database at the Norwegian Information Security Laboratory using two different cell phone cameras, namely the Nokia N95 and HTC Desire where details mentioned later.

E.2 Fingerprint Recognition

Fingerprint recognition is the most matured approach among all the biometric techniques ever discovered. With its success of use in different applications, it is today used in many access controls applications as each individual has an immutable, unique fingerprint. The hand skin or the finger skin consists of the so called friction ridges with pores. The ridges are already created in the ninth week of an individuals fetal development life [4], and remains the same all life long, only growing up to adult size, but if severe injuries occur the skin may be reconstructed the same as before. Researchers have found out that identical twins have fingerprints that are quite different and that in the forensic community it is believed that no two people have the same fingerprint [19].

Many capture device technologies have been developed over the last decades replacing the old ink imaging process. The old process was based on sensing ridges on an individuals finger with ink, where newer technologies uses a scanner placing the surface of the finger onto this device. Such technologies are referred to as live-scan and based on four techniques [14]:

Frustrated total internal reflection (FTR) and optical methods is a first live scan technology. Figure E.1 illustrates, how the reflected signal is acquired by a camera from the underside of a prism when a finger touches the top of the prism. The typical image acquisition surface of 1 inch by 1 inch is converted to 500 dots per inch (DPI) using either charge coupled device (CCD) or complementary metal oxide semiconductor (CMOS) camera.

CMOS Capacitance. The ridges and valleys create different charge accumulations, when a finger hits a CMOS chip grid. This charge is converted to an intensity value of a pixel using various competing techniques such as alternating current (AC), direct current (DC) and radio frequency (RF). The typical image acquisition surface of 0.5 inch by 0.5 inch is converted to 500 dots per inch (DPI). The resultant images also have a propensity to be affected by the skin dryness and wetness.

Ultrasound Sensing. The thermal sensor is developed by using pyro-electric material, which measures temperature changes due to the ridge-valley structure as the finger is swiped over the scanner and produces an image. In this case the skin is a better thermal conductor than air and thus contact with the ridges causes a noticeable temperature drop on a heated surface. This technology is claimed to overcome the dryness and wetness of the skin issues of optical scanners. But the resulting images are not affluent in gray value images. The thermal sensor is becoming more popular today, because they are small and of low cost. Swipe sensors based on optical and CMOS technology are also available as commercial products.

Figure E.2: Left: CMOS Sesnor (HTC Desire), Right: CMOS Sensor (Nokia N90) and a cropped/contrasted fingerprint image from each cell, at the same scale factor.

E.3 Data Collection

E.3.1 Rationale

Besides fingerprint recognition systems deployed for applications with high-security requirements such as border control [12, 1] and forensics [8], fingerprint recognition is supposed to be promising for consumer markets as well for many years [6, 5]. In the meanwhile, privacy concerns over fingerprint recognition technologies' deployment in non-high-security applications have been raised [11, 3] and thus leads to a refrained development of biometrics in consumer market in recent years compared with the rapid development in the public sectors such as border control, critical infrastructure's access control, and crime investigations.

We suppose there are at least two ways to alleviating these privacy concerns. Biometric template protection [17, 7] is one of the most promising solutions to provide a positive-sum of both performance and privacy for biometric systems' users. The European Research Project TURBINE [2] demonstrated a good result in both performance and privacy of the ISO fingerprint minutiae template based privacy-enhancement biometric solutions. On the other hand, for the consumer market, we think using customers' own biometric sensors will also help alleviate the customers' privacy concerns. That is the motivation of this paper to try using cell phone cameras as sensors for fingerprint sample collection.

Obviously, for applications requiring high security, subjects' own biometric sensors may not be suitable for data collection unless the cell phone can be authenticated as a registered and un-tampered device in both software and hardware aspects, which is difficult to realize for a normal consumer electronics that is out of the control of the inspection party. However for consumer market, cell phone can be deemed nowadays as a secure device accepted by many customers, e.g, many banking services send transaction password, TAN code or PIN code via SMS to customers' cell phone. So in this paper we assume biometric data collection by the customers' cell phone cameras will not raise more privacy and security concerns to the customers than the cell phone based banking services.

In the meanwhile we expect technical challenges in quality control to the cell phone camera captured samples, especially from the sample image processing aspects such as bias lighting conditions and unstable sample collection environment caused by hand-holding. In addition, most existing cell phone cameras are not designed for biometric use and accurate focusing will always be a challenge for fingerprint image capturing. We address these potential challenges in this paper in a simplified way to investigate whether cell phone camera can generate good quality samples and corresponding good biometric performance in a relative stable data collection environment.

E.3.2 Data Collection Steps

As there is no standard benchmark database available for fingerprint images captured by digital camera, we constructed an independent database. The image database is comprised of 22 subjects from which fingerprint images were taken with a cell phone camera. The fingerprint data used in this paper are captured by two commercial sensors as shown in Figure E.2. The cell cameras used were Carl Zeiss Optics from Nokia N95 and HTC Desires' embedded camera. Further detailed information of the sensors is described in Table E.1.

The constructed independent database comprises of 1320 fingerprint images. These images stem from 220 finger instances, where each instance was captured 6 times. The images are stored in the internal memory of the phones and all the images were collected in the cameras "Burst Mode". For evaluating the performance of various

Cell Phone	**Nokia N95**	**HTC Desire**
Lens Type	**CMOS, Tessar lens**	**CMOS**
Mega Pixel	5.0	5.0
Resolution	2592x1944	2592x1552
Flash	LED Flash	LED Flash
ISO Speed	100 - 800	52
Auto-Focus	Yes	Yes

Table E.1: Cell phone camera setting for fingerprint image acquisition.

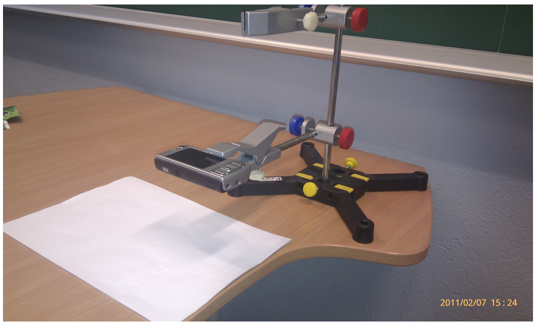


Figure E.3: Setup for the Nokia N95 capture device.

algorithms under different settings, the Nokia N95 was fixed placed on a hanger as illustrated in Figure E.3 where images were taken by a human operator holding the phone and capturing images for the HTC Desire. The image capture was performed inside a laboratory with normal lighting conditions.

E.4 Evaluation

As can be seen in Figure E.4, the user initially presents its biometric characteristic (i.e., capturing the fingerprint) to the sensor equipment (i.e. camera in a mobile phone), which captures it as captured biometric sample. After preprocessing this captured sample, features will be extracted from the sample. In case of fingerprint biometrics, these features would typically be minutia points. The extracted features can then be used for comparison against corresponding features stored in a database, based on the claimed identity of the user. The result of the comparison is called the *similarity score* S, where a low value of S indicates little similarity, while a high value indicates high similarity. The last step is to compare the similarity score S to a predefined system *threshold* T, and output a decision based on both values. In case the similarity score is above the threshold ($S > T$) then the user is accepted as genuine, while a similarity score below the threshold ($S < T$) indicates an impostor who is rejected by the system. Obviously the biometric features of the user must initially be stored in the database before any comparison of a probe feature vector can take place. This is done during the *enrolment phase*. During the enrolment biometric samples are captured from the biometric characteristic, after which it is processed and features are extracted. The extracted data is now stored in a database and linked to the identity of the user who enrolled. The stored data in the database is referred to as the *reference template* of the user. In case of fingerprint biometrics it is a common approach to derive the features from multiple captured samples and generate a single minutiae template.

E.4.1 Feature Extraction

In order to measure the sensor performance we have applied the Neurotechnology, Verifinger 6.0 Extended SDK commercial minutia extractor for the feature extraction. The SDK includes functionality to extract a set of minutiae data from an individual fingerprint image and to compute a comparison-score by comparing one set of minutiae data with another. Both SDKs support open and interoperable systems as the generated minutiae templates can be stored according to the ISO or ANSI interchange standard.

E.4.2 Feature Comparison

We compared the verification results of the Neurotechnology algorithm on the processed images. For each algorithm the error rates were determined based on a threshold separating genuine and impostor scores. The False Match Rate (FMR) and False None-Match Rate (FNMR) were calculated. The calculation of FMR and FNMR is

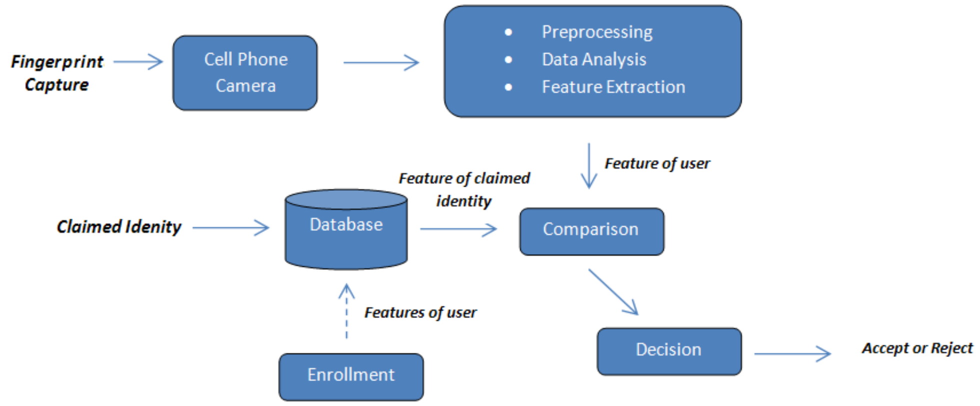


Figure E.4: A traditional verification process.

done in the following way. We have collected N data samples from each of M participants, then we have calculated similarity scores between two samples, either stemming from one finger instance or from two different instances. A similarity score between two samples from the same source is called a genuine score, while an impostor score is the similarity score between two samples from different instances. Given our setting, we can have $N * M$ data samples from which we can calculate the total number of $N_{Gen} = \frac{M*N*(N-1)}{2}$ different genuine scores and $N_{Imp} = \frac{M*N*(M-1)*N}{2}$. Given these sets of genuine and impostor scores we can calculate FMR and FNMR for any given threshold T as follows:

$$FMR(T) = \frac{Number\ of\ incorrectly\ accepted\ impostor\ images \geq T}{Total\ number\ of\ impostor\ images} \tag{E.1}$$

$$FNMR(T) = \frac{Number\ of\ incorrectly\ rejected\ genuine\ images < T}{Total\ number\ of\ genuine\ images} \tag{E.2}$$

From this, we can find the point where FNMR equals FMR, or in other words the Equal Error Rate (EER). This rate is very common used value which is being used to compare different systems against each other, and it roughly gives an idea of how well a system performs.

The images that were generated with the mobile phones encode the finger position according to Table E.2 and the equal error rates retrieved corresponding to the finger codes are overviewed in Table E.3

Finger Position	Code
Right thumb	1
Right index finger	2
Right middle finger	3
Right ring finger	4
Right little finger	5
Left thumb	6
Left index finger	7
Left middle finger	8
Left ring finger	9
Left little finger	10

Table E.2: Finger position codes according to ISO 19794-2.

In general we see that the left index finger (code 7) has performed best for both phones with EER of 0.0% and 8.47%. The overall performance (cross comparison of all ten fingers) which can be seen in column *all* for Nokia N95 performs significantly better than the Desire. This is so because of various reasons. The Nokia was placed in fixed way on the holder while capturing. Furthermore, the Nokia was set to an internal close-up mode

Cell Phone	1	2	3	4	5	6	7	8	9	10	all
Nokia N95:	5.77	5.92	5.11	7.36	5.43	2.98	0.0	0.43	6.26	5.45	4.66
HTC Desire:	11.73	11.43	23.62	21.17	16.01	10.98	8.47	15.37	16.11	15.96	14.65

Table E.3: EERs of cell phone fingerprint recognition. Numbers are in percentage.

setting. This mode is ideal for capturing details of small objects within a distance between 10 and 60 cm. Here we had to ensure that the auto-focus always resulted in better quality images at a small distance when capturing the fingerprints, whereas the HTC was manually adjusted by the human operator. Thus, this means that the Nokia N95's auto-focus was performing slightly better than the HTC Desire.

E.5 Discussion

Since personal mobile devices at present time only offer means for explicit user authentication, this authentication usually takes place one time; only when the mobile device has been switched on. After that the device will function for a long time without shielding user privacy. As of today the majority of Internet users are expecting a transparent transition of services from the wired to the wireless mobile world. As personal mobile devices such as Apple's iPhone, T-Mobile's G1 or Nokia's S60 become more popular the ordinary user is expecting and using the full range of Internet services in the mobile Internet, since former limitations with regard to screen size and interaction capabilities (zooming, ”copy and paste” functionality etc.) disappeared recently. In fact many users are even extending their expectations from their home and office environment, as they enjoy typical mobile features, such as location-based services, which are supported by widespread GPS-features.

On the contrary users tend to ignore the risks, which they accept while operating Internet services from their mobile device. Not only sensitive information is accessible from the mobile device but also transactions on the stock market and other critical services, which grant access to financial assets. At the same time mobile devices are more exposed to the public and thus there is likelihood that a mobile device is lost or stolen in an unattended moment. This threat is shown by the number of approx. 10.000 mobile phones, which were left in London taxis every month in 2008 [13].

It is obvious that a mobile Internet can only exist, if there is a strong link between the mobile device and the authorized user of that specific device. This requires that proper access control mechanisms are in place, to control that the registered user and only the registered user operates the mobile device. Unfortunately most mobile devices are operated today with knowledge-based access control only, which is widely deactivated due to the associated inconvenience.

A promising way out of these pressing problems is to implement on mobile devices secure biometric access control mechanisms, which provide a non-reputable approach based on the observation of biological characteristics (i.e. the fingerprint) of the registered user. The aim of a biometric access control process is, to determine whether the biometric characteristic of the interacting subject and the previously recorded representation in the reference data match.

A possible application scenario of a the fingerprint biometric user verification system in a mobile device could be as follows; When a device such as a mobile phone, is first taken into use it would enter a ”practicing” learning mode where the high quality fingerprints data are processed and stored. Password-based or PIN code user authentication would be used during the learning session. If the solidity fingerprint biometrics was sufficient enough, the system would go into a biometric authentication ”state”, a state that will need confirmation from the owner. In this state the system would asynchronously verify the owner's identity every time the owner wanted to authenticate.

E.6 Conclusion

The cell phone camera database has been used to study the performance of some fingerprint verification algorithms in a first step towards real-life situations. The database has scaled and posed distortions in addition to illumination. The camera lens' cause further distortion in the images with changes in orientation.

The novel biometric method for frequent authentication of users of mobile devices proposed in this paper was investigated in a technology test. It contained fingerprints data. The recognition resulted in different performances of using one minutia extractor and comparator. The best algorithm performance gained resulted in an EER of 4.66.% for the Nokia N95. Looking forward into which finger was performing best, then we observe an EER of 0.0% for the left index finger as well.

The shown results suggest the possibility of using the proposed method for protecting personal devices such as PDAs, smart suitcases, mobile phones etc. In a future of truly pervasive computing, when small and inexpensive hardware can be embedded in various objects, this method could also be used for protecting valuable personal items. Moreover, reliably authenticated mobile devices may also serve as an automated authentication in relation to other systems such as access control system or automated external system logon.

E.7 Acknowledgments

We would like to thank Simon McCallum and Jayson David Mackie for using their cell phones for the experiment. Furthermore, we would like to thank all volunteers participating in the data collection.

E.8 Bibliography

[1] 2004/512/ec: Council decision of 8 june 2004 establishing the visa information system (vis). http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:32004D0512:EN:NOT. [Online; accessed 13-February-2011]. 205, 214

[2] Eu fp7 integrated project - trusted revocable biometric identities. http://www.turbine-project.org/. [Online; accessed 13-February-2011]. 205, 214

[3] Europe tells britain to justify itself over fingerprinting children in schools. http://www.telegraph.co.uk/news/worldnews/europe/eu/8202076/Europe-tells-Britain-to-justify-itself-over-fingerprinting-children-in-schools.html. [Online; accessed 13-February-2011]. 205, 214

[4] Fetal development. http://www.pregnancy.org/fetaldevelopment. [Online; accessed 13-February-2011]. 204, 211

[5] Fingerprint biometric retail pos systems on show. http://www.prosecurityzone.com/News/Biometrics/Fingerprint_recognition/Fingerprint_biometric_retail_pos_systems_on_show_16250.asp #axzz1Dr8cNsOu. [Online; accessed 13-February-2011]. 205, 214

[6] Fingerprint payment heads for the uk. http://www.talkingretail.com/news/industry-news/fingerprint-payment-heads-for-the-uk. [Online; accessed 13-February-2011]. 205, 214

[7] *ISO/IEC FDIS 24745 Information technology – Security techniques – Biometric information protection, FDIS, Feb. 2011.* 205, 214

[8] Method for fingerprint identification. http://www.interpol.int/public/Forensic/ fingerprints/WorkingParties/IEEGFI/ieegfi.asp. [Online; accessed 13-February-2011]. 205, 214

[9] Mobile phone theft increasing across the uk. http://www.insure4u.info/home-insurance-mobile/mobile-phone-theft-increasing-across-the-uk.html. [Online; accessed 30-March-2011]. 203

[10] Nist image group's fingerprint research. http://www.itl.nist.gov/iad/894.03/fing/ fing.html. [Online; accessed 13-February-2011]. 203, 212

[11] Retailers fingerprint plans prompt privacy concerns. http://www.computing.co.uk/ctg/news/1826631/retailers-fingerprint-plans-prompt-privacy-concerns. [Online; accessed 13-February-2011]. 205, 214

[12] Safety & security of u.s. borders: Biometrics. http://travel.state.gov/visa/immigrants/info/info_1336.html. [Online; accessed 13-February-2011]. 205, 214

[13] Security park: 60,000 mobile phones left in london taxis in the last six months. http://www.securitypark.co.uk/security_article262056.html. [Online; accessed 13-February-2011]. 208

[14] Bolle, R., Connell, J., Pankanti, S., Ratha, N., and Senior, A. *Guide to Biometrics*. SpringerVerlag, 2003. 204

[15] Gafurov, D., Bours, P., Yang, B., and Busch, C. Guc100 multi-scanner fingerprint database for in-house (semi-public) performance and interoperability evaluation. *Computational Science and its Applications, International Conference* (2010), 303–306. 203, 212

[16] Hiew, B. Y., Teoh, A. B. J., and Yin, O. S. A secure digital camera based fingerprint verification system. *J. Vis. Comun. Image Represent. 21* (April 2010), 219–231. Available from: `http://dx.doi.org/10.1016/j.jvcir.2009.12.003`. 204, 212

[17] Jain, A. K., Nandakumar, K., and Nagar, A. Biometric template security. *EURASIP J. Adv. Signal Process 2008* (January 2008), 113:1–113:17. Available from: `http://dx.doi.org/10.1155/2008/579416`. 205, 214

[18] Mueller, R., and Sanchez-Reillo, R. An approach to biometric identity management using low cost equipment. *Intelligent Information Hiding and Multimedia Signal Processing, International Conference on* (2009), 1096–1100. 204, 212

[19] Pankanti, S., Prabhakar, S., and Jain, A. K. On the individuality of fingerprints. *IEEE Trans. Pattern Anal. Mach. Intell. 24* (August 2002), 1010–1025. Available from: `http://portal.acm.org/citation.cfm?id=605089.605091`. 204, 212

[20] Shah, S. U., e Hadi, F., and Minhas, A. A. New factor of authentication: Something you process. *Future Computer and Communication, International Conference on* (2009), 102–106. 203

Appendix F

Biometric Access Control using Near Field Communication and Smart Phones

Abstract

Near Field Communication or NFC is a short-range communication channel that is one of the most promising technologies around. One of the purposes for this technology is to simplify first-time connections to other wireless technologies, like Wi-Fi and Bluetooth. In this article we will show how Near Field Communication in a Samsung Nexus S smartphone can be used as part of a two-factor access control system for unlocking a door. Biometric Fingerprint recognition is used for authentication and NFC will be used to transmit authentication information to computer controlling the door. We will define some requirements for the system to increase security and propose some solutions for implementation to improve protection of biometric assets.

F.1 Introduction

Authentication in smart phones is an area which has grown over the last decades, and will continue to grow in the future. It is used in many places today and being authenticated has become a daily habit for most people. Examples of this are PIN code, pattern password or biometrics. We identify friends and family by their face, voice, how they walk, etc. Many possible mobile biometrics applications require the transmission of information in the form of biometric templates or identification information, such as business, cards between phones at close physical proximity. Near Field Communication (NFC) is proposed as a solution that is considered the most human-centric or user-friendly and the quickest for the passing of small amounts of data at close range.

NFC is a wireless short range communication technology, allowing us to transfer over a distance of up to 10 cm, but typically around 0-4 cm in practical. The major advantage of NFC compared to other wireless technology is its simplicity. Simply by touching a reader, another NFC device or a NFC compliant tag, transactions are initialized automatically. With applications like using it as a contactless credit card or as a contactless bus ticket, or establishing Bluetooth or Wi-Fi connections by touching a tag, NFC technology gives additional functionality to a mobile device. Estimations show that by 2012 there are about 180 million mobile devices (equivalent to 20 % penetration) equipped with this technology [25]. Because of its close proximity and automatic transfer with an access point, it will make the process of setting up and transfer of the network settings easier and more secure.

In this article we introduce NFC in a access control scenario, where people can get quick access to their homes on their mobile devices by using either their biometric characteristics or a PIN, thus deploying a two-factor authentication scheme based on biometric traits or knowledge and the possession of a token. For the biometrics part, we have chosen to work with an Android Phone(HTC Desire) and a Symbian phone(Nokia N95), where as for the NFC implementation we have used the Samsung Nexus S. Due to late arrival of the NFC-enabled Samsung Nexus S phone we did not have the opportunity to execute the fingerprint recognition experiment on that. However, the NFC implementation and the the fingerprint recognition part are independent of eachother. The Samsung Nexus S is the only NFC-enabled android phone of the ones used in this article.

F.2 Related Work

F.2.1 Biometric Smart-Phone recognition (BSR)

Biometric recognition related to smartphones is increasing. The most related work on BSR system uses the camera device for fingerprint recognition [20], face recognition (Android 4.0) and accelerometer sensors for gait recognition [19]. In this section we focus at the first mentioned, namely how a BSR system using fingerprint is possible.

Fingerprint recognition is the most matured approach among all the biometric techniques ever discovered. With its success of use in different applications, it is today used in many access controls applications as each individual has an immutable, unique fingerprint. The hand skin or the finger skin consists of the so called friction ridges with pores. The ridges are already created in the ninth week of an individuals fetal development life [4],

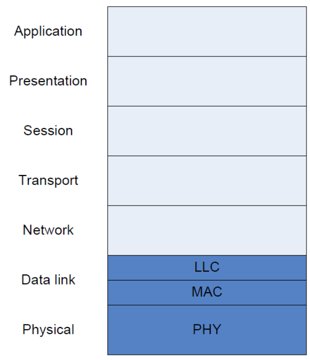


Figure F.1: NFC in the OSI model.

and remains the same all life long, only growing up to adult size, but if severe injuries occur the skin may be reconstructed the same as before. Researchers have found out that identical twins have fingerprints that are quite different and that in the forensic community it is believed that no two people have the same fingerprint [27].

Many fingerprint recognition algorithms perform well on databases that had been collected with high-resolution cameras and in highly controlled situations [14]. Recent publications show that the performance of a baseline system deteriorates from Equal Error Rate (EER) around 0.02 % with very high quality images to EER = 25 % due to low qualities images [21]. Thus active research is still going on to improve the recognition performance. In applications such as fingerprint authentication using cameras in cell phones and PDAs, the cameras may introduce image distortions (e.g., because of fish-eye lenses), and fingerprint images may exhibit a wide range of illumination conditions, as well as scale and pose variations. An important question is which of the fingerprint authentication algorithms will work well with fingerprint images produced by cell phone cameras?

However, recent research [26, 22] have shown that by using low-cost webcam devices it is possible to extract fingerprint information when applying different pre-processing and image enhancements approaches. In this paper we present fingerprint recognition as means of verifying the identity of the user of a mobile phone [20].

F.2.2 Near Field Communication

NFC is a short range communication standard developed by NFC Forum [12], which is a nonprofit organization. This forum consists of cooperation between several participants and is working in four different groups where they specialize in hardware, applications, security and testing.

NFC is based on RFID, and the underlying magnetic field induction technology restricts the range of the communication to typically 0-2 centimeters, and maximum up to ten centimetres. It is a successor to early stage of smartcard technology found in Sony FeliCa and Phillips MIFARE. NFC operates in the unlicensed and globally available ISM band of 13.56MHz.

RFID and NFC are basically using the same working standards, but as mentioned the NFC standard restrict the range with use of magnetic field induction. In addition to contact less smart cards (ISO14443), which only support communication between powered devices and passive tags, NFC also provides peer-to-peer communication. NFC combines the feature to read out and emulate RFID tags and to share data between electronic devices that both have active power.

The data rates within the distances can be up to 424 Kbps depending on the tag specification. It also depends on what kind of coding schemes implemented and modulation techniques used. Similar technologies for short range communication include Bluetooth and TransferJet. We do not discuss these technologies in this thesis because they are not relevant to our security discussion, but instead refers to them for interested readers.

The purpose of NFC is to exchange information or establish a connection between two units (both between devices, like two mobile phones, or between a device and a tag, e.g. a mobile phone and a smart card), with a simple ”touch”, where the devices are close enough to perform a communication session without any form of configuration. The information exchanged between devices and/or tags could be used for identification, authentication, and exchange of data or setup of other communication links.

In principle a NFC device contains an RFID reader/writer which is integrated into the user device with a host controller interface, developed for NFC support. The limitation of using areas of this standard lies in the application framework, since the standard is very ”general”. It can be used in many different areas, like for example bootstrapping of other communication standards, exchange of small amount of information, door locks, payment machines, ticketing, cars, TVs and so on.

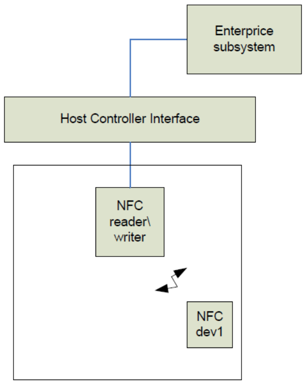


Figure F.2: System Architecture of a Near Field Communication System.

F.2.2.1 Standards

NFC is described in the protocols NFCIP-1 and NFCIP-2 (Near Field Communication Interface and Protocol 1 and 2). NFCIP- is standardized in ISO18092 , ECMA 340 and ETSI TS 102 190. It is composed of a physical layer and data link layer, as illustrated in Figure F.1 with blue color. This protocol specifies different functions for the RF device. It defines the active and passive communication modes. It specifies modulation schemes, coding, transfer speed and frame format for the interface. The protocol also defines initializing schemes and conditions for collision control.

F.2.2.2 System Architecture

Typical system architecture of a Near Field Communication system is illustrated in Figure F.2. A NFC communication is based on point to point, and therefore the two devices can communicate at the same time. The figure illustrates a NFC device 1, which want to initiate a connection with the NFC system, which contains a NFC reader/writer. This system is further connected to a host controller interface (HCI) which is an interface between the NFC system and an enterprise subsystem.

F.2.2.3 Communication Modes

The NFC interface can operate in two different communication modes; passive and active. In the active mode both devices are active and generate their own RF field. In passive mode the passive device must use inductive coupling to transmit data.

In passive mode, a passive device can be powered by the RF field of an active NFC device and transfer data using load modulation. The passive devices do not require an internal power recourse, which means that in scenarios where an NFC mobile phone is used for payment, the phone does not require battery to use the NFC device.

In active mode, both NFC devices are generating their own RF fields when they want to send data. Only one of the devices can generate an RF field and send data at a time, therefore no duplex functionality is implemented.

Generally, only two devices can communicate at the same time, but in passive communication mode the initiator (which is active) is able to communicate to several passive devices at the same time. This is realized by a time slot method, which is used to perform a Single Device Detection (SDD). The maximum number of time slots is limited to 16. A target responds in a random chosen time slot that can lead to collision with the response of another target. In order to reduce the collisions, a target may ignore a polling request set out by the initiator. If the initiator does not receive any response, it has to send the polling request again [23].

F.2.2.4 Initiator and Target

NFC defines two different modes for a device in a given session. One of the communication participants are the initiator and the other is the target.

The initiator is the one who wants to communicate and initiates the communication. The target receives the initiators communication request and sends back a reply. This concept prevents the target from sending any data without first receiving a request message from the initiator. Regarding the passive communication mode, the passive device acts always as the NFC target. In this case the active device is the initiator, which is responsible for generating the RF field. In the case of an active configuration in which the RF field is alternately generated, the roles of initiator and target are strictly assigned to the one who starts the communication. By default, all devices are NFC targets and only act as a NFC initiator device if it is required by the application. It is not possible to initiate communication between an initiator and a target where both devices are passive. This is because none of the devices would be able to generate any RF field. Therefore none of them are able to either request or respond to any messages [23].

F.2.2.5 NFC Connection Scenerios

There are four possible scenarios for setting up a Near Field Communication which involve different types of units, described in table 1 and illustrated below. The tag is typically used to receive configuration settings from an AP and exchange these settings with a NFC enabled WLAN device for setting up the wireless network. The tags will not be further described in this paper, but only illustrated for the scenario and example purposes.

1. Access Point ↔ NFC tag
2. Mobile NFC device ↔ NFC enabled Access Point
3. Mobile NFC device ↔ NFC tag
4. Mobile NFC device ↔ Mobile NFC device

F.2.2.6 Collision Avoidance

In order to not disturb any other NFC communication or any current infrastructure running on the carrier frequency, an Initiator shall not generate its own RF field as long as another RF field is detected. To start communication with the Target device, either in the Active or the Passive communication mode, an Initiator shall sense the presence of an external RF field.

If the Initiator do not detect any RF field within a given timeframe, the RF field shall switch on. In addition to the initial RF Collision Avoidance, an RF collision avoidance response during activation shall be required in the Active communication mode. This is to avoid collision of data by simultaneous response from more than one target. A more detailed specification of the collision avoidance can be found in the NFCIP-1 specification [23].

F.3 Implementation, Analysis and Evaluation

F.3.1 Fingerprint Recognition

F.3.1.1 Rationale

Besides fingerprint recognition systems deployed for applications with high-security requirements such as border control [18, 1] and forensics [10], fingerprint recognition is supposed to be promising for consumer markets as well for many years [6, 5]. In the meanwhile, privacy concerns over fingerprint recognition technologies' deployment in non-high-security applications have been raised [17, 3] and thus leads to a refrained development of biometrics in consumer market in recent years compared with the rapid development in the public sectors such as border control, critical infrastructure's access control, and crime investigations.

We suppose there are at least two ways to alleviating these privacy concerns. Biometric template protection [24, 8] is one of the most promising solutions to provide a positive-sum of both performance and privacy for biometric systems' users. The European Research Project TURBINE [2] demonstrated a good result in both performance and privacy of the ISO fingerprint minutiae template based privacy-enhancement biometric solutions. On the other hand, for the consumer market, we think using customers' own biometric sensors will also help alleviate the customers' privacy concerns. That is the motivation of this paper to try using cell phone cameras as sensors for fingerprint sample collection.

Obviously, for applications requiring high security, subjects' own biometric sensors may not be suitable for data collection unless the cell phone can be authenticated as a registered and un-tampered device in both software and hardware aspects, which is difficult to realize for a normal consumer electronics that is out of the control of the inspection party. However for consumer market, cell phone can be deemed nowadays as a secure device accepted by many customers, e.g, many banking services send transaction password, TAN code or PIN code via SMS to customers' cell phone. So in this paper we assume biometric data collection by the customers' cell phone cameras will not raise more privacy and security concerns to the customers than the cell phone based banking services.

In the meanwhile we expect technical challenges in quality control to the cell phone camera captured samples, especially from the sample image processing aspects such as bias lighting conditions and unstable sample collection environment caused by hand-holding. In addition, most existing cell phone cameras are not designed for biometric use and accurate focusing will always be a challenge for fingerprint image capturing. We address these potential challenges in this paper in a simplified way to investigate whether cell phone camera can generate good quality samples and corresponding good biometric performance in a relative stable data collection environment.

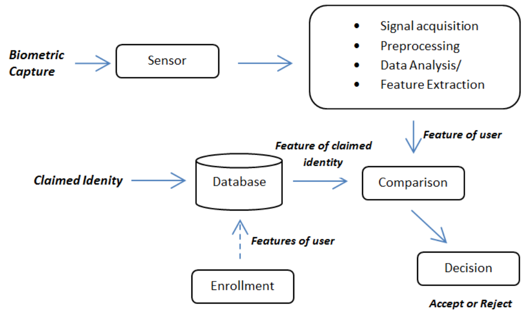


Figure F.3: A traditional verification process.

F.3.1.2 Data Collection Steps

As there is no standard benchmark database available for fingerprint images captured by digital camera, we constructed an independent database. The image database is comprised of 22 subjects from which fingerprint images were taken with a cell phone camera. The fingerprint data used in this paper are captured by two commercial sensors.

The cell cameras used were Carl Zeiss Optics from Nokia N95 and HTC Desires' embedded camera. Further detailed information of the sensors is described in Table F.1.

Cell Phone	**Nokia N95**	**HTC Desire**
Lens Type	**CMOS, Tessar lens**	**CMOS**
Mega Pixel	5.0	5.0
Resolution	2592x1944	2592x1552
Flash	LED Flash	LED Flash
ISO Speed	100 - 800	52
Auto-Focus	Yes	Yes

Table F.1: Cell phone camera setting for fingerprint image acquisition.

The constructed independent database comprises of 1320 fingerprint images. These images stem from 220 finger instances, where each instance was captured 6 times. The images are stored in the internal memory of the phones and all the images were collected in the cameras "Burst Mode".

For evaluating the performance of various algorithms under different settings, the Nokia N95 was fixed placed on a hanger where images were taken by a human operator holding the phone and capturing images for the HTC Desire. The image capture was performed inside a laboratory with normal lighting conditions.

As can be seen in Figure F.3, the user initially presents its biometric characteristic (i.e., capturing the fingerprint) to the sensor equipment (i.e. camera in a mobile phone), which captures it as captured biometric sample. After preprocessing this captured sample, features will be extracted from the sample. In case of fingerprint biometrics, these features would typically be minutia points. The extracted features can then be used for comparison against corresponding features stored in a database, based on the claimed identity of the user. The result of the comparison is called the *similarity score* S, where a low value of S indicates little similarity, while a high value indicates high similarity. The last step is to compare the similarity score S to a predefined system *threshold* T, and output a decision based on both values. In case the similarity score is above the threshold ($S > T$) then the user is accepted as genuine, while a similarity score below the threshold ($S < T$) indicates an impostor who is rejected by the system. Obviously the biometric features of the user must initially be stored in the database before any comparison of a probe feature vector can take place. This is done during the *enrollment phase*. During the enrollment biometric samples are captured from the biometric characteristic, after which it is processed and features are extracted. The extracted data is now stored in a database and linked to the identity of the user who enrolled. The stored data in the database is referred to as the *reference template* of the user. In case of fingerprint biometrics it is a common approach to derive the features from multiple captured samples and generate a single minutiae template.

F.3.1.3 Feature Extraction

In order to measure the sensor performance we have applied the Neurotechnology, Verifinger 6.0 Extended SDK commercial minutia extractor for the feature extraction. The SDK includes functionality to extract a set of minutiae data from an individual fingerprint image and to compute a comparison-score by comparing one set of minutiae

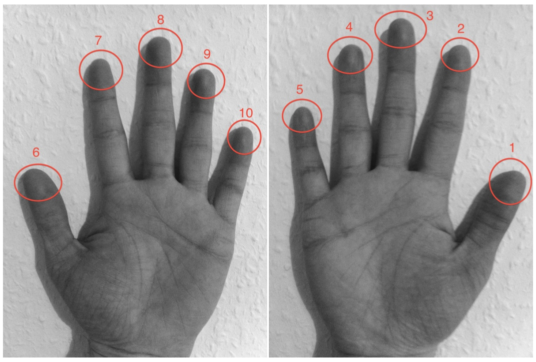


Figure F.4: Finger position codes according to ISO 19794-2.

data with another. Both SDKs support open and interoperable systems as the generated minutiae templates can be stored according to the ISO or ANSI interchange standard.

F.3.1.4 Feature Comparison

We compared the verification results of the Neurotechnology algorithm on the processed images. For each algorithm the error rates were determined based on a threshold separating genuine and impostor scores. The False Match Rate (FMR) and False None-Match Rate (FNMR) were calculated. The calculation of FMR and FNMR is done in the following way. We have collected N data samples from each of M participants, then we have calculated similarity scores between two samples, either stemming from one finger instance or from two different instances. A similarity score between two samples from the same source is called a genuine score, while an impostor score is the similarity score between two samples from different instances. Given our setting, we can have $N * M$ data samples from which we can calculate the total number of $N_{Gen} = \frac{M*N*(N-1)}{2}$ different genuine scores and $N_{Imp} = \frac{M*N*(M-1)*N}{2}$. Given these sets of genuine and impostor scores we can calculate FMR and FNMR for any given threshold T as follows:

$$FMR(T) = \frac{incorrectly\ accepted\ impostor\ images \geq T}{total\ number\ of\ impostor\ images}$$

$$FNMR(T) = \frac{incorrectly\ rejected\ genuine\ images < T}{total\ number\ of\ genuine\ images}$$

From this, we can find the point where FNMR equals FMR, or in other words the Equal Error Rate (EER). This rate is very common used value which is being used to compare different systems against each other, and it roughly gives an idea of how well a system performs.

The images that were generated with the mobile phones encode the finger position according to Figure F.4 and the equal error rates retrieved corresponding to the finger codes are overviewed in Table F.2

In general we see that the left index finger (code 7) has performed best for both phones with EER of 0.0% and 8.47%. The overall performance (cross comparison of all ten fingers) which can be seen in column *all* for Nokia N95 performs significantly better than the Desire. This is so because of various reasons. The Nokia was placed in fixed way on the holder while capturing. Furthermore, the Nokia was set to an internal close-up mode setting. This mode is ideal for capturing details of small objects within a distance between 10 and 60 cm. Here we had to ensure that the auto-focus always resulted in better quality images at a small distance when capturing the fingerprints, whereas the HTC was manually adjusted by the human operator. Thus, this means that the Nokia N95's auto-focus was performing slightly better than the HTC Desire.

	Nokia N95	HTC Desire
1	5.77	11.73
2	5.92	11.43
3	5.11	23.62
4	7.36	21.17
5	5.43	16.01
6	2.98	10.98
7	0.0	8.47
8	0.43	15.37
9	6.26	16.11
10	5.45	15.96
all	4.66	14.65

Table F.2: EERs of cell phone fingerprint recognition. Numbers are in percentage.

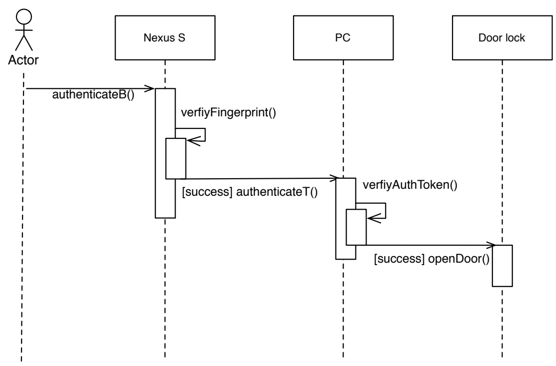


Figure F.5: Nexus S as a two-factor authentication door key

F.3.2 Near Field Communication

F.3.2.1 Using a Nexus S smart phone as a two-factor authentication door key

NFC technology has been integrated into smart phones for years, without seeing broad adoption by the mass market. This is about to change as feature phones are increasingly replaced by smart phones, which enable more interesting and complex usage scenarios. One of the key scenarios has always been mobile payment, which is getting more momentum again, with Google offering the new Wallet service [7], which integrates the Nexus S smart phones NFC technology with the MasterCard PayPass service.

In this work we used a Nexus S smart phone with android version 2.3.4 and an ACR122U NFC reader that was connected to a desktop PC running Ubuntu 11.04. Additionally the PC was connected to the electrical door opener with a relay. In the chosen usage scenario, a user has to take a picture of his finger with the built-in camera and tap the NFC reader with his smart phone afterwards to open a door. If the verification of the fingerprint image fails, the phone will not send the required authentication token to the NFC reader at the door. The usage scenario is depicted in the sequence diagram in Figure F.5.

NFC is supported by the android operating system beginning with version 2.3.1 (API level 9). Tags are automatically recognized and read and the according NDEF messages (NMs) are dispatched to an activity that registered for that type of message. The API also provides functions to write NMs to various types of tags. Starting with API level 10 (android 2.3.3), Peer to Peer (P2P) data exchange is supported with the NDEF Push Protocol (NPP)[11]. The NPP is implemented as a service on top of LLCP and is addressable with the service name "com.android.npp". The NPP specification is available on the android website. As we used a NFC reader to communicate with the phone, P2P

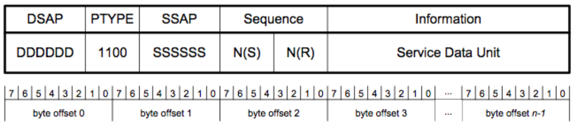


Figure F.6: Information PDU format [13]

communication over NPP was the natural choice.

Every android application, that wants to use the NFC API has to define the following permission in its manifest file:

Listing F.1: Request NFC permission

```
<uses-permission android:name="android.permission.NFC"/>
```

Next, a NM should be created and initialized with a NdefRecord (NR) that contains the authentication token for the door. We used a static token in order to avoid developing an application for the desktop PC, where devices could be registered and an access control list (ACL) could be managed. The following code example demonstrates the creation of such a NM:

Listing F.2: Creating a NdefMessage

```
NfcManager nfcm = (NfcManager) getSystemService(NFC_SERVICE);
mAdapter = nfcm.getDefaultAdapter();
myNdefMessage = new NdefMessage(new NdefRecord[] { newTextRecord("
    device_auth_token", Locale.ENGLISH, true) });
mAdapter.enableForegroundNdefPush(this, myNdefMessage);
```

The newTextRecord method converts the message to the UTF-8 encoding. The operating system now automatically sends the NM as an NDEF Entry (NE) in the NPP packet as soon as the LLCP link is established. The activity which registered the NdefPush message has to be active in the foreground.

On the desktop side we built and installed libnfc, libnfc-llcp, the acsccid driver for the ACR122U NFC reader from ACS and the following required software packages and dependencies:

- autotools (packages: autoconf, automake, libtool)
- libusb-dev [9]
- PCSC-Lite [16]
- libpcsclite-dev
- OpenSC [15]

We used version 1.7.0 of PCSC-Lite, because the latest version did not work with the latest version of libnfc and the NFC reader. The libnfc-llcp library includes a demonstration program which creates a LLCP service with either connectionless or connection-oriented transport. Connection-oriented transport is characterized by the establishment of a data link connection and the subsequent acknowledgement of received packets. In connectionless transport mode, no such connection establishment or packet acknowledgement takes place. The android NFC stack uses the connection-oriented transport mode, so we set-up a connection-oriented server on the desktop side and disabled the creation of a connectionless server.

In order to receive NDEF messages sent by an android device, the LLCP service shall be bound the service name "com.android.npp". This service name, which is defined in the NPP specification from Google, does not conform to the service name URI specification from the NFC Forum and thus is not well-formed. The NPP payload, a Service Data Unit (SDU), is stored in the information field of the Information Protocol Data Unit (Information PDU), which is depicted in Figure F.6.

An NPP packet consists of a header and one or more NEs. The header has a field for the NPP protocol version and a field for the number of NEs, followed by the NEs. Each NE contains an action code, the length of the NM in bytes and the NM itself. The layout of a NPP packet is depicted in Figure F.7.

The NE structure is depicted in Figure F.8.

Every NM consists of one or more NRs. The layout of a typical NR is depicted in Figure F.9.

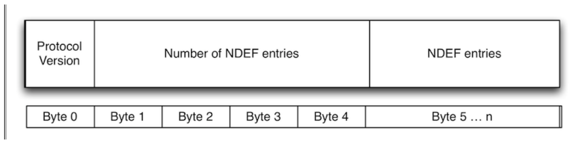


Figure F.7: NPP packet format as described in version 1 of NPP

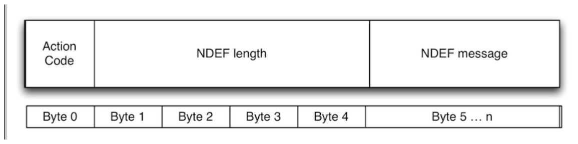


Figure F.8: NDEF Entry format as described in version 1 of NPP

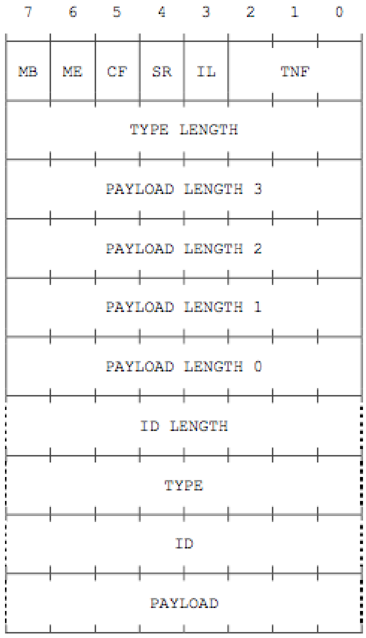


Figure F.9: NDEF Record layout [13]

The specification defines two different record types: the normal record format includes four octets for the payload length field, while the short record format includes only one octet for the payload length field, requiring that the payload size does not exceed 256 octets. When the short record format is used, the Short Record (SR) flag shall be set.

At the time the LLCP service is initialized, we set a callback for the server thread. This thread listens on the incoming queue and proceeds as soon as a PDU is received. If the received PDU is an Information PDU, we inspect the payload and check for the NPP protocol version and number of NEs. The actual payload offset can be determined by summing up the header sizes. The NPP header has one byte for the protocol version and four bytes for the number of NEs. In the first version of NPP only one NE is allowed. An NE has one byte for the action code and four bytes for the length of the following NM. So 10 bytes are already used by the NPP protocol. The NDEF record can either have six or nine bytes for the header, depending on the type of record (normal or short record). This sums up to 16 or 19 bytes, depending on the type of NR. As we send a very short authentication token that fits in a single NR, we can directly jump to the offset in the received packet and read the token.

This design should only be used for demonstration purposes. Additional security measures should be applied in real world applications. A communication channel over NFC is not secure by default, so to prevent eavesdropping or replay attacks a higher level security scheme like SSL should be deployed. Furthermore, centralized account management with features like privilege revocation is desirable.

F.4 Conclusion

We have measured the performance of fingerprint recognition based on images from digital cameras in smart phones. The results indicate that especially the autofocus algorithms should be improved in order for the feature extraction to yield better results. We integrated this experiment into a realistic usage scenario, where the fingerprint recognition is combined with token-based authentication. We have shown that a Nexus S smart phone, which features a 5MP digital camera and a NFC chip, can be used as a two-factor authentication door key. We gave a brief description of NFC technology and protocols and a protocol for P2P communication over NFC and how we used this technology to build a token-based authentication model. The concept is currently implemented as a prototype, where a Nexus S smart phone is used as a token to open a door.

F.5 Acknowledgments

We would like to thank Pål Erik Endrerud and Hans Pedersveen for helping us with the setup of the electronic part.

F.6 Bibliography

[1] 2004/512/ec: Council decision of 8 june 2004 establishing the visa information system (vis). http://eur-lex.europa.eu/. [Online; accessed 29-September-2011]. 205, 214

[2] Eu fp7 integrated project - trusted revocable biometric identities. http://www.turbine-project.org/. [Online; accessed 29-September-2011]. 205, 214

[3] Europe tells britain to justify itself over fingerprinting children in schools. http://www.telegraph.co.uk/news/worldnews/europe/eu/ 8202076/Europe-tells-Britain-to-justify-itself-over-fingerprinting-children-in-schools.html. [Online; accessed 13-February-2011]. 205, 214

[4] Fetal development. http://www.pregnancy.org/fetaldevelopment. [Online; accessed 13-February-2011]. 204, 211

[5] Fingerprint biometric retail pos systems on show. http://www.prosecurityzone.com/News/Biometrics/ Fingerprint_recognition/Fingerprint_biometric_retail_pos_systems_on _show_16250.asp #axzz1Dr8cNsOu. [Online; accessed 13-February-2011]. 205, 214

[6] Fingerprint payment heads for the uk. http://www.talkingretail.com/news/industry-news/fingerprint-payment-heads-for-the-uk. [Online; accessed 13-February-2011]. 205, 214

[7] Google wallet. http://www.google.com/wallet/. [Online;September 28, 2011]. 217

[8] *ISO/IEC FDIS 24745 Information technology – Security techniques – Biometric information protection, FDIS, Feb. 2011.* 205, 214

[9] libusb. http://www.libusb.org/. [Online;September 28, 2011]. 218

[10] Method for fingerprint identification. http://www.interpol.int/public/Forensic/ fingerprints/WorkingParties/IEEGFI/ieegfi.asp. [Online; accessed 13-February-2011]. 205, 214

[11] Ndef push protocol specification. http://source.android.com/compatibility/ndef-push-protocol.pdf. [Online;September 28, 2011]. 217

[12] Nfc-forum. http://www.nfc-forum.org. [Online; accessed 29-September-2011]. 212

[13] Nfc forum specifications. http://www.nfc-forum.org/specs/. [Online;September 28, 2011]. xii, 218, 219

[14] Nist image group's fingerprint research. http://www.itl.nist.gov/iad/894.03/fing/ fing.html. [Online; accessed 13-February-2011]. 203, 212

[15] Opensc. http://www.opensc-project.org/opensc. [Online;September 28, 2011]. 218

[16] Pcsc-lite. http://pcsclite.alioth.debian.org/pcsclite.html. [Online;September 28, 2011]. 218

[17] Retailers fingerprint plans prompt privacy concerns. http://www.computing.co.uk/ctg/news/1826631/retailers-fingerprint-plans-prompt-privacy-concerns. [Online; accessed 13-February-2011]. 205, 214

[18] Safety & security of u.s. borders: Biometrics. http://travel.state.gov/visa/immigrants/info/info_1336.html. [Online; accessed 13-February-2011]. 205, 214

[19] DERAWI, M. O., NICKEL, C., BOURS, P., AND BUSCH, C. Unobtrusive user-authentication on mobile phones using biometric gait recognition. In *IIH-MSP* (2010), pp. 306–311. 211

[20] DERAWI, M. O., YANG, B., AND BUSCH, C. Fingerprint recognition with embedded cameras on mobile phones. *3rd International ICST Conference on Security and Privacy in Mobile Information and Communication Systems, MobiSec, 2011.* (May 2011). 211, 212

[21] GAFUROV, D., BOURS, P., YANG, B., AND BUSCH, C. Guc100 multi-scanner fingerprint database for in-house (semi-public) performance and interoperability evaluation. *Computational Science and its Applications, International Conference* (2010), 303–306. 203, 212

[22] HIEW, B. Y., TEOH, A. B. J., AND YIN, O. S. A secure digital camera based fingerprint verification system. *J. Vis. Comun. Image Represent. 21* (April 2010), 219–231. Available from: `http://dx.doi.org/10.1016/j.jvcir.2009.12.003`. 204, 212

[23] HOLIEN, K. Security in NFC with Wi]Fi Protected Setup as a use, Master thesis, University of Agder, 2008. 213, 214

[24] JAIN, A. K., NANDAKUMAR, K., AND NAGAR, A. Biometric template security. *EURASIP J. Adv. Signal Process 2008* (January 2008), 113:1–113:17. Available from: `http://dx.doi.org/10.1155/2008/579416`. 205, 214

[25] MADLMAYR, G., LANGER, J., KANTNER, C., AND SCHARINGER, J. Nfc devices: Security and privacy. In *ARES* (2008), pp. 642–647. 211

[26] MUELLER, R., AND SANCHEZ-REILLO, R. An approach to biometric identity management using low cost equipment. *Intelligent Information Hiding and Multimedia Signal Processing, International Conference on* (2009), 1096–1100. 204, 212

[27] PANKANTI, S., PRABHAKAR, S., AND JAIN, A. K. On the individuality of fingerprints. *IEEE Trans. Pattern Anal. Mach. Intell. 24* (August 2002), 1010–1025. Available from: `http://portal.acm.org/citation.cfm?id=605089.605091`. 204, 212

Appendix G

Participant Agreement Declaration

Participation in acquisition of gait data

I am participating in the acquisition of gait data on a voluntarily basis. The data are taken using accelerometers in mobile devices to fulfill the purpose that is described in detail on the back side of this sheet.

The data processing institutions are the Gjøvik University College (Hgskolen i Gjøvik). These institutions take care that the recorded data are solely used for teaching and research purposes.

With my signature I confirm the following:

1. I have been informed in oral and written form about the content and purpose of the collected data that is in relation to my person.
2. My data will only be used to serve this purpose. The detailed description of the purpose is documented on the back side of this sheet.
3. I allow that gait data from me are collected.
4. I have been informed that I can reject to sign the agreement.
5. I have been informed that I can request to receive insight in the collected data before such data is used for teaching and research purposes.
6. I know that I can withdraw my participation anytime I want without giving any explanation and all data collected from we will be deleted permanently.

All data will be deleted respectively the link between the data and my name will be destroyed as soon as it is not necessary to maintain it. This will happen as the research experiment has been completed.

First name - family name:

Gender:

Age:

Height (in cm):

Weight (in kg):

Lenght of leg (in cm):

Kind of worn shoes):

Time, Date and Signature:

Background information for this agreement

Purpose of this project

From each participant we capture video data while the participant is walking.

The data will be used for the following purpose: Provision of data to the biometric research groups in the Gjøvik University College. The data will be stored and analyzed without link to the name of the student but with the research relevant meta data such as age and gender.

Background information

The recorded data will be used to develop and test methods which allow the authentication on mobile devices by gait recognition. Data on mobile devices is often insufficiently protected as it is more comfortable for the user to stay logged-in. This means that anybody having physical access to the mobile device can directly access all data stored in it. This shows the need for user-friendly authentication methods which enable an unobtrusive authentication.

A second focus is on technology research for enabling privacy protection of the stored references (so called biometric templates) in a biometric system. Since biometric technologies are widely adopted in multiple applications, the threat of compromising the biometric templates becomes ever more serious. Based on earlier studies it is expected that this research will lead to new technological measures that allows for templates that prevent the possibility for cross-matching and associated data mining, and allows for renewability in case the biometric record is compromised. The data set will be used to validate the scientific research results. It will be taken care that no attempt is being made to analyze the captured signals regarding diseases or personal characteristics and habits of the subject. For the purpose of this research project it is only of relevance, whether or not recognition can be performed with high reliability.

Appendix H

Data Acquisition, Statistics and Methods

This appendix discuss information and methods used throughtout the chapters 4 - 11.

H.1 Data Acquisition

This section gives an overview of the equipments applied and the statistics of the databases created and used. In total, four datasets have been created from three different phones (Datasets 1 -4) and one dataset was used for performance evaluation (Dataset 5). The phones used are illustrated in Figure H.1 and the information of the datasets are given in Table H.1.

Figure H.1: Left: Google G1, Middle: Motorola Milestone, Right: Samsung Nexus S

	Dataset 1	**Dataset 2**	**Dataset 3**	**Dataset 4**	**Dataset 5**
Sensor	G1 Phone	Milestone	Milestone	Nexus S	MR100
Subjects	51	48	45	25	60
Output Rate	40 - 50	80	80	120	100
Placement	Hip	Hip	Hip	Hip	Hip
Environment	Indoor	Indoor	Indoor	Indoor	Indoor
Distance	37 m	240 m	27 m	29	20
Used in	[8]	[13]	[5]	[6]	[7]

Table H.1: Number of participants and gender information for each dataset.

H.1.1 Speed Issues

All datasets, whether the data was used for gait or for activity recognition, have had the same conditions. No fixed pace was given, so the walking speed varies from subject to subject depending on what the subject interpreted to be his/her normal, slow, or fast walking. It is believed that by prescribing a particular speed to a subject will result in an unnatural way of walking with too much focus at the speed.

H.2 Statistics

This section gives an overview of the gender, age, weight, height and 'length of leg' statistics in Table H.2 to Table H.6 for the created datasets. All 'Participant Agreement Declaration' forms were collected and an overview from that has been made. Unfortunately it is not all forms that were filled up with all information or eventually missing, thus a Not Available (N/A) attribute is written.

	No./subjects	% Male	% Female
Dataset 1	51	N/A	N/A
Dataset 2	48	62.5 %	37.5 %
Dataset 3	45	67 %	33 %
Dataset 4	25	88 %	12 %

Table H.2: Number of participants and gender information for each dataset.

	Average age	Std.Dev	Min. age	Max age
Dataset 1	28.8	N/A	N/A	N/A
Dataset 2	29.5	8.8	22	59
Dataset 3	25.9	9.4	9	59
Dataset 4	31.1	6.9	21	60

Table H.3: Age statistics

	Average weight [kg]	Std.Dev	Min. weight [kg]	Max weight [kg]
Dataset 1	N/A	N/A	N/A	N/A
Dataset 2	72.5	16.2	45	140
Dataset 3	71.8	17.5	30	120
Dataset 4	N/A	N/A	N/A	N/A

Table H.4: Weight statistics

	Average height [cm]	Std.Dev	Min. height [cm]	Max height [cm]
Dataset 1	N/A	N/A	N/A	N/A
Dataset 2	174.2	8.5	156	193
Dataset 3	173.8	10.1	140	197
Dataset 4	N/A	N/A	N/A	N/A

Table H.5: Height statistics

	Average lenght of leg [cm]	Std.Dev	Min. lenght [cm]	Max lenght [cm]
Dataset 1	N/A	N/A	N/A	N/A
Dataset 2	97.7	7.2	84	112
Dataset 3	98.9	8.3	84	114
Dataset 4	N/A	N/A	N/A	N/A

Table H.6: Lenght of leg statistics.

H.3 Methods

H.3.1 Gait Recognition Methods

The human walking pattern consists of multiple repeated gait cycles. Each gait cycle contains two steps. Listed below are all the feature extraction and comparison methods applied within the chapters 4 - 11.

H.3.1.1 Feature Extraction

Preprocessing

First, the preprocessing applies the *linear time interpolation* on the three axis data (x,y,z) retrieved from the sensor to obtain a observation every equally fixed amount of seconds - for example, every $\frac{1}{100}$ seconds - since the time intervals between two observation points are not always equal.

A weakness from the sensor is the fact that the acceleration data will be outputted with some noise. This noise is reduced by using a noise reduction filter, e.g. the *weighted moving average* filter.

Thereafter, the data values are converted to g-forces by using properties of the sensor. And finally we calculate the resultant vector or the so-called magnitude vector by applying the following formula,

$$r_t = \sqrt{x_t^2 + y_t^2 + z_t^2}, t = 1, ..., N$$

where r_t, x_t, y_t and z_t are the magnitudes of resulting, vertical, horizontal and lateral acceleration at time t, respectively and N is the number of recorded observations in the signal.

Cycle Detection

Each accelerometer outputs data a specific sample rate. In newer mobile phones the sample rates are between 80 - 120 samples per second. One gait cycle, will approximately also take a second to perform, thus it follows that one cycle-length varies between $60 - 140$ samples depending on the speed of the person. An estimation of how long one cycle is can be calculated. This is done by extracting a small subset of the data and compare that subset with other subsets of similar length. Based on the distance scores between the subsets, the average cycle length is computed.

The cycle detection starts from a minimum point, P_{start}, around the center of the walk. From this point, cycles will be detected in both directions. By adding the average length, denoted γ to P_{start}, the estimated ending point $E = P_{start} + \gamma$ is retrieved (in opposite direction: $E = P_{start} - \gamma$). The cycle end is defined to be the minimum in the interval Neighbour Search (see [7]) from the estimated end point. This process is repeated from the new end point, until all cycles are detected.

Template Creation

The last step of the feature extraction is to create the feature vector template. Here we ensure to skip cycles that are very different from the others. This is performed by taking each cycle and calculate its distance to every other cycle by using dynamic time warping (DTW),

$$dtw_{i,j} = dtw(cycle_i, cycle_j)$$

where i = 1..N and j = 1..N, which means that we will get a symmetric N $\times$ N matrix. From this point, we calculate all the averages of one specific cycle to all others.

$$d_i = \frac{1}{n-1} \sum_{j \neq i} dtw_{i,j}$$

We calculate the mean, μ, and the standard deviation, σ, from the set of d_i

$$d_i = [\mu - 2\sigma; \mu + 2\sigma]$$

The factor 2 in 2σ is determined by trial and error. A lower limit resulted in skipping too many cycles, while a higher limit would lead to not skipping some of the irregular cycles.

When all irregular cycles are removed, a feature vector is created. The feature vector can be a simple one-dimensional vector consisting of one average cycle (e.g. the mean or median cycle) or multi-dimensional vector consisting of multiple cycles (e.g. keeping all extracted cycles).

H.3.1.2 Feature Comparators

During comparison, distances between stored references and probes have to be computed. Two feature vector comparators have been created, namely the Cyclic Rotation Metric and Cross-DTW Metric (CDM). Below these are described in details. Also the more common Manhattan and Euclidean distance are described, as well as the Majority Voting Scheme.

Manhattan

The Manhattan distance also known as absolute distance is given in the Equation below

$$d_{Manhattan}(X, Y) = \sum_{i=1}^{k} |x_i - y_i|$$

This is a simple metric that takes the sum of the absolute values of the differences between all the values in the template and the corresponding values in the probe. As a result of this, Manhattan distance requires that the template and the input have equal length. In addition, this distance metric is computationally the least expensive one.

Euclidean

The Euclidean distance is a slightly modified version of to the Manhattan and is given by Equation below.

$$d_{Euclidean}(X, Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

The Euclidean distance is defined as the distance between two points defined as the square root of the sum of the squares of the differences between the corresponding coordinates of the points. As a result of this, Euclidean distance requires that the template and the input have equal length.

Dynamic Time Warping [12]

The dynamic time warping (DTW) is a well-known technique to find an optimal alignment between two given (time-dependent) sequences under certain restrictions. A cost matrix C is computed, which is based on cost for substitution, deletion and insertion.

Cyclic Rotation Metric (CRM)

For this distance, the cycles have to be of equal length, l. The probe cycle is cyclically rotated l times. For each rotated version of the probe the Manhattan distance is calculated to the template. The minimal Manhattan distance together with the DTW distance of the corresponding cycles is the final distance pair. Two thresholds are applied in the classification process, one for each distance. At least one of them has to be lower than the corresponding threshold.

Cross-DTW Metric (CDM)

As a first step, the locations of the minima of the probe cycle are computed. The cycle is rotated, such that each of these minima is once the cycle start. For each rotated cycle p_i, the DTW distance is computed. The minimum of these distances is the final distance between the two cycles: CDM($r; p$) = min_i(DTW($r; p_i$)), where i = 1,..,n and n is the number of computed minima in the probe cycle.

Majority Voting

Comparison is done using DTW as distance function and applying majority voting: The distances of the reference cycle to all probe cycles are computed. If the distance between two cycles is below a pre-selected threshold this is called a match, otherwise a non-match. If at least 50% of the results are a match, the whole comparision is assumed to be a match and the subject is authenticated.

H.3.2 Activity Recognition Methods

To process only meaningful data, it is necessary to identify those parts of the collected data where a subject is walking. In general, this can be done by applying activity recognition methods. In this section we will state the applied methods and their parameters.

H.3.2.1 Feature Extraction

The cyclke extraction methods that have been applied for gait recognition are also applied here. The actual featues which are selected for a further process are based on the cycles extracted. The features used for activity recognition are stated:

Mean Mean value of the cycle.

Median Median value of the cycle.

Min Minimal value of the cycle.

Max Maximal value of the cycle.

Std Standard deviation of the cycle.

Clen Cycle Lenght of the cycle.

H.3.2.2 Classifications

Several different machine learning algorithms for classification were evaluated and identified to deliver suitable results for accelerometer-based activity recognition. These algorithms are very briefly presented with a reference and its given parameters applied. All of these methods have in common, that they need to be trained during enrollment, i.e. supervised learning algorithms. For the calculation of the accuracy an open source software WEKA (Waikato Environment for Knowledge Analysis)) has been applied. This workbench contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces. It supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, and feature selection.

Support Vector Machines [3]

The support vector Machines parameters used in WEKA are shown in Table H.7

Parameter	Value
SVMType	C-SVM)
kernel type	$exp(-gamma * \|u - v\|^2)$
kernel degree	3
eps (terminate tolerance)	0.001
gamma	0

Table H.7: LibSVM parameters in WEKA

MultilayerPercepton [9]

The multilayerPercepton parameters used in WEKA are shown in Table H.8

Parameter	Value
hidden layers	(features + classes) / 2
learning rate	0.3
momentum	0.2

Table H.8: MLP parameters in WEKA

Radial Basis Function Network [14]

The radial basis function network parameters used in WEKA are shown in Table H.9

Parameter	Value
minStdDev	0.1
numClusters	2
ridge	1.0E-8

Table H.9: RBFNetwork parameters in WEKA

Bayesian network [4]

The bayesian network parameters used in WEKA are shown in Table H.10

Parameter	Value
alpha (estimator)	0.5 (simple)
score type	BAYES
maxNrofParent	1

Table H.10: Bayesian network parameters in WEKA

NaiveBayes [11]

There naivebayes are no parameters set in WEKA for this algorithm,

RandomTree [2]

The randomtree parameters used in WEKA are shown in Table H.11.

Parameter	Value
KValue	0
maxDepth	0
minNum	1.0
numFolds	0

Table H.11: RandomTree parameters in WEKA

Logistic Model Trees [10]

Parameter	Value
minNumInstances	15
weightTrimBeta	0.0
numBoostingIterations	-1

Table H.12: LMT parameters in WEKA

H.3.3 Parameters Affecting the Performance

This thesis work did not make any contribution on which factors might have an affect of the gait performance. However, some of these factors have been described in a study by Boyd and James [1]. Even though the gait cycle is primarily determined by the skeletal measurements of an individual such as leg length, thigh length, foots size etc, the gait cycle described in the background chapter can be altered significantly by other parameters such as injury and muscle development. For example, a person who has had a sports injury walks completely differently to someone who is fit and healthy. Even a slight muscular discomfort can alter the gait cycle and therefore for applications of gait in authentication presents an added complication. Another parameter that might affect is training, such as those undertaken by ballet dancers changes the way they walked previously. Even when a person gets tired or fatigue issues, there is a dissimilarity in the walking cycle that could affect gait analysis. By wearing different footwear, it has been shown that that muscle activation in walkers changes when people walk bare foot as opposed to wearing shoes. The gait cycle may also be affected by culture issues. For example, if a subject achieves a high position such as manager of an organization he/she will modify the walking style to reflect his/her new status and factor that may confound biometric gait recognition. Each of these factors may confound biometric gait recognition.

H.4 Bibliography

[1] BOYD, J., AND LITTLE, J. Biometric gait recognition. In *Advanced Studies in Biometrics*, M. Tistarelli, J. Bigun, and E. Grosso, Eds., vol. 3161 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg, 2005, pp. 19–42. Available from: `http://dx.doi.org/10.1007/11493648_2`. 231

[2] BREIMAN, L., AND ADELE. Random trees. Available from: `http://docs.opencv.org/modules/ml/doc/random_trees.html`. 230

[3] CHANG, C.-C., AND LIN, C.-J. LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology 2* (2011), 27:1–27:27. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`. 229

[4] CHEN, Y., AND LIGINLAL, D. Bayesian networks for knowledge-based authentication. *IEEE Trans. on Knowl. and Data Eng. 19*, 5 (May 2007), 695–710. Available from: `http://dx.doi.org/10.1109/TKDE.2007.1024`. 230

[5] DERAWI, M. O., BAJRAMI, G., AND BOURS, P. Gait and activity recognition using smart phones. *International Conference on Pervasive Computing, Signal Processing and Applications* (2011). 56, 57, 225

[6] DERAWI, M. O., AND BOURS, P. Gait and activity recognition using commercial phones. *Submitted to Special Issue of Computers & Security on Active Authentication* (2012). 56, 57, 225

[7] DERAWI, M. O., BOURS, P., AND HOLIEN, K. Improved cycle detection for accelerometer based gait authentication. In *International Conference on Intelligent Information Hiding and Multimedia Signal Processing - Special Session on Advances in Biometrics* (2010). 25, 27, 29, 54, 57, 225, 227

[8] DERAWI, M. O., NICKEL, C., BOURS, P., AND BUSCH, C. Unobtrusive user-authentication on mobile phones using biometric gait recognition. *International Conference on Intelligent Information Hiding and Multimedia Signal Processing* (2010), 306–311. 54, 57, 225

[9] GURNEY, K. *An Introduction to Neural Networks*. Taylor & Francis, Inc., Bristol, PA, USA, 1997. 229

[10] LANDWEHR, N., HALL, M., AND FRANK, E. Logistic model trees. *Mach. Learn. 59*, 1-2 (May 2005), 161–205. Available from: `http://dx.doi.org/10.1007/s10994-005-0466-3`. 230

[11] LEWIS, D. D. Naive (bayes) at forty: The independence assumption in information retrieval. In *Proceedings of the 10th European Conference on Machine Learning* (London, UK, UK, 1998), ECML '98, Springer-Verlag, pp. 4–15. Available from: `http://dl.acm.org/citation.cfm?id=645326.649711`. 230

[12] MÜLLER, M. *Dynamic Time Warping - Information Retrieval for Music and Motion*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2007. 228

[13] NICKEL, C., DERAWI, M., BOURS, P., AND BUSCH, C. Scenario test for accelerometer-based biometric gait recognition. In *International Conference on Security and Communication Networks (IWSCN)* (2011). 55, 57, 225

[14] ORR, M. J. L. Introduction to radial basis function networks, 1996. 230

Index

Acceptability, 10
Accuracy, 14
Authentication, 7, 12

Background and Related Work, 7
Behavioural, 8
Biometric systems, 10
Biometrics, 9
Body based, 7

Circumvention, 10
Collectability, 9
comparator, 13
Comparison, 13
Comparison subsystem, 11

Data capture subsystem, 11
Data storage subsystem, 11
Decision subsystem, 12
Distinctiveness, 9

Enrollment phase, 12
error types, 13

Floor Sensor Based, 18
Fundamental concepts, 9

Gait Recognition, 17

Identification, 12
Introduction, 1

Knowledge based, 7

Moving Average, 24
Multi-Factor Authentication, 8

Noise reduction, 23

Object based, 7

Performance, 9
Permanence, 9
Physiologica, 8

resultant vector, 22

Signal processing subsystem, 11

Universality, 9

Verification, 12
Video Sensor Based, 17

Wearable-Sensor Based, 18
Weighted Moving Average, 24