NTNU
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Gait Mimicking

Attack Resistance Testing of Gait Authentication Systems

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Problem Description

(Composed by the student)
Biometrics is the science of using physiological and behavioral characteristics (e.g. fingerprints, iris, retina, voice) to recognize individuals. One of the latest advances in biometrics is the use of human gait for recognition.

The student's task is to test the security strength of gait biometrics against spoofing attacks (i.e. imitation / mimicking). This implies that the student should become very familiar with the field of gait biometrics, investigate existing and develop new analysis methods, build a software tool for gait recognition, and finally conduct an experiment that involves mimicking attacks analysed by this software.

Some minimal-effort mimicking has been attempted in earlier research. The student should present this, and justify the need for further research on the same topic. The experiment should involve some form of training and feedback of test subjects, and try to determine whether it is possible to learn to walk like someone else.

Assignment given: 22. January 2009
Supervisor: Danilo Gligoroski, ITEM

Abstract

Biometric technology is rapidly evolving in today's society. A large part of the technology has its roots hundreds, or even thousands of years back in time, while other parts are new and futuristic. Research suggest that individuals can be identified by the way they walk, and this kind of biometrics, gait biometrics, is a rather new and definitely intriguing field. However, the technology is far from mature; the performance is not generally competitive to other biometrics, and it has not been thoroughly tested security-wise.

This thesis aims to test the security strength of gait biometrics. It will focus on imitation, or mimicking of gait. The bottom line question is whether it is possible to learn to walk like someone else. If this turns out to be easy, it will have a severe effect on the potential of gait as an authentication mechanism in the future.

The report is logically twofold. In one part, the reader is brought up to speed on the field of gait biometrics, and a software tool for gait authentication is developed and presented. Second, an experiment is conducted, involving extensive training of test subjects, and using sources of feedback like video and statistical analysis. The data is analyzed by regression, and the goal is to determine whether or not the participants are increasing their mimicking skills, or simply put: if they are *learning*.

The first part of the experiment involves 50 participants that are successfully enrolled using the developed software. The results compete with state of the art gait technology, with an EER of 6.2%. The rest of the experiment is related to mimicking, and the thesis discovers that six out of seven participants seem to have a natural boundary to their performance, a "plateau", forcing them back whenever they attempt to improve further. The location of this plateau predetermines the outcome of an attack; for success it has to lie below the acceptance threshold corresponding to the EER. Exactly one such boundary is identified for almost all participants, but some data also indicate that more than one plateau can exist simultaneously.

The final result however, is that a very limited amount of learning is present, not nearly enough to pose a threat to gait biometrics. Gait mimicking is a hard task, and our physiology works against us when we try to adopt specific gait characteristics.

Preface

This thesis represents the finalization of my studies at the Norwegian University of Science and Technology in Trondheim, NTNU. Through internships and studies both in Norway and in the US, I have been fortunate to discover a field within information security in which I have vast interest - biometrics. I feel privileged having been able to compose the problem description myself, based on my own ideas and interests.

First off I want to thank my tutor, Patrick Bours, who helped me out in such a dedicated manner that I cannot imagine reaching half as far as I did without him.

My supervisor at NTNU, Danilo Gligoroski, also deserves my thanks - he was especially important to my motivation, as he has a special way of always making you think you are doing something of great importance. I hope he was right.

Secondly, I wish to give big thanks to those who participated in my experiments, who's anonymity I must preserve. Especially I want to thank those who spent hours of training for the more extensive parts, without even showing a hint of boredom.

I had to move to Gjøvik for some time in order to conduct my experiments. I would like to express my gratitude to the Department of Telematics at NTNU for covering my extra expenses in this period.

This thesis is dedicated to my mother.

Sincerely,

Bendik B. Mjaaland
June 4, 2009

”No man ever yet became great by imitation.”

Dr. Samuel Johnson

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Chapter 1

Introduction

1.1 Background

Imagine someone approaching you from several hundred meters away. All you can see is the dark silhouette of a person, no details are visible. Now imagine the task of trying to recognize this individual, without using a telescope or similar optical devices to zoom in. What sources of biometrics would you use? Face, fingerprint and retina scans are of course impossible from this range, all you can see is a human like shape moving towards you.

In some scenarios with wide-area monitoring this is a plausible situation, and it constitutes an example of where physical biometrics cannot be used efficiently. So we turn to behavioral biometrics, and ask ourselves if the way the individual walks is enough to determine its identity.

During the summer of 2008 the author of this thesis attended Accenture's Summer Internship program in Oslo, working on a project that involved fingerprint biometrics. Shortly after, he was so inspired by this project that he made biometrics the topic of his main research project at NTNU. The work that summer involved innovative fingerprint technology - biometric encryption, or biocryptics, which the author developed his own methods for the same fall [38, 39].

Obviously, it is not a coincidence that this thesis is also about biometric technology. However, the author found many interesting biometric traits to research upon, and eventually felt like focusing on something new. Fingerprint biometrics is, historically, ”old news”, and the author find some of the emerging biometric technologies quite intriguing.

Gait, as a biometric trait, has an innovative, futuristic touch. Imagine a stolen cell phone that recognizes that the current user is not its actual owner, and locks down asking for a password. Or imagine a video camera or a floor carpet outside your office that recognizes your gait and opens the door as you approach.

As we shall see, gait can be recorded and analyzed in various ways. However, the goal of this thesis will not be to establish that it is possible to let a computer recognize people by their gait, that has already been done. The author will instead team up with the adversaries and impostors, and try to find out whether or not it is possible to *imitate* the gait of enrolled users, and thus fool a biometric system into producing a false accept.

If it proves to be easy to learn how to walk like someone else, then gait authentication loses much value. The author chooses this topic not to make other scientists' earlier efforts in the field futile, but to put the biometric trait to the test in the same way all traits should be. If we never enter the mind of an attacker, how can we predict and prevent hostile acts?

1.2 Method

The thesis work was conducted in collaboration between the Norwegian University of Science and Technology (NTNU) in Trondheim and Gjøvik University College (HiG). The main part of the research took place at NTNU. The author obtained material mostly from reviewed sources on the Internet, along with the student library at NTNU and previous work by students at HiG. Since Gjøvik has an especially strong academic community within biometrics, parts of the work was done there, in particular the experiment and data analysis was conducted in this area. MATLAB was used as the main tool for implementation.

1.3 Scope and Objectives

This thesis seeks to establish whether or not it is possible to ”forge” gait, in order to fool a gait authentication system, by extensively training test subjects to walk like a well chosen victim. This forging, or spoofing, is best described as imitation or mimicking, which explains the title: ”Gait Mimicking - Attacking biometric technology based on human gait”.

The report presents basic biometric theory, its applications, challenges and related work in the field. The main topic is gait, more specifically; the main topic is one specific threat against gait biometrics: mimicking. Earlier attempts are discussed, and the design of a new, more extensive experiment is presented. The data from the experiment is analyzed to see if it is possible to extract indicators on whether or not imitation constitutes a serious threat to gait biometrics.

As later chapters will clarify, gait biometrics is not an entirely new concept - it has already been proven that a biometric system can recognize an individual on its gait. Some minimal effort mimicking attempts have already been done. This thesis concentrates on mimicking, but involves much more training of the test subjects than what has previously been seen in research. Attempts are made to derive learning curves from the results. One may hope that the learning curves found are flat, and that all attempts to imitate gait looks rather random - indicating that nothing is improving, even under training. However, despite the hopes of not finding pessimistic indicators, the experimenting is, naturally, performed without any bias.

It is convenient to look at specific research questions, and three interesting ones in this context are:

- Will extensive training of individuals affect their ability to mimic gait?
- Is mimicking easier for an individual who's normal gait is similar to the victim?
- What kind of feedback and available sources of information affects the performance of an impostor's mimicking?

1.4 Outline

Chapter 2 introduces basic biometric theory, biometric system design, and challenges related to both general biometrics and its corresponding systems. An introduction to authentication as a security service is also an important part of this chapter, including biometrics as a mechanism for this purpose.

Chapter 3 introduces gait as a biometric feature. The current state of the art is presented, with special focus on spoof attacks on gait recognition. Hardware related topics are presented, such as different gait collecting technology, as well as different paths to take when analyzing the data. The chapter is intended to show the user that previous research has already made a lot of headway, but also that more work needs to be done - especially to test the security of gait biometrics.

Chapter 4 presents the thesis' choice of technology in detail. Bits and pieces from previous research are combined and tailored for best performance provided these choices. The resulting scheme is implemented in MATLAB, as a complete gait analysis software tool.

Chapter 5 marks the end of theory, and the start of the experimenting phase. This chapter goes through the experiment design - how the author plans to conduct each scenario of the experiment, where and with whom. Terminology for the experiment is established, and detailed sets of participant instructions are presented using this terminology. A framework for the attacker training is also an important part of this chapter.

Chapter 6 presents the experiment results. The experiment consists of several scenarios - the friendly scenario results are given with DET curves, and the hostile scenarios are covered with walkthroughs and some remarks based on first impressions. Most of the discussion is left for the proceeding chapters.

Chapter 7 provides the main analysis of the collected data, and discussions related to the findings. The most important part of this chapter is the statistical analysis, where each attacker's result is evaluated in terms of a regression model. Another regression is also performed on the residuals from the first, verifying the fit of the regression model. All this is aimed towards the discovery of learning curves - a fitted curve that shows us where the results are going while the training is conducted. Sticky points, defined in the thesis as *plateaus*, are identified. Confidence intervals and hypothesis testing are the tools used to ensure fit and certainty. The results from this analysis are used to answer to the initial objectives of the thesis.

Chapter 9 draws conclusions from, and sums up the thesis work. It also suggests future research topics in the area of gait biometrics.

1.5 Abbreviations, Notations and Terms

Biometrics is used, depending on the context, either as the technology of recognizing bodily characteristics of an individual, or as the characteristics themselves.

Features, (Biometric) are characteristics of a biometric trait (e.g. a fingerprint) that can be used to describe it, in other words - points of interest. However, in some contexts it can also be used as the biometric trait in its entirety.

Gait is a persons manner of walking [56]. Human gait is a complex biological process that involves nervous and musculo-skeletal systems [58].

Identifiers, (Biometric) are biometric traits that all individuals possess, and can tell one individual apart from all others.

Inter (-class) used loosely in this thesis to describe variations in biometric samples for different individuals. A biometric identifier should ideally exhibit high inter-class variation (high level of uniqueness).

Intra (-class) used loosely in this thesis to describe variations in biometric samples for the same person. A biometric identifier should ideally exhibit low intra-class variation (high level of stability / permanence).

Plateaus are states or periods of little or no change following a period of activity or progress" [16]. Used in this thesis to describe a natural limit to learning, where a participant experiences resistance when trying to gain particular skills.

Templates, (Biometric) are data sets in a database, each describing the features of one particular biometric image.

Traits, (Biometric) are bodily characteristics that might be able to identify a person, sometimes in literature referred to as indicators, identifiers or modalities.

DET Decision Error Tradeoff

DTW Dynamic Time Warping

EER Equal Error Rate

FAR False Acceptance Rate

FFT Fast Fourier Transform

FMR False Match Rate

FNMR False Non-Match Rate

FRR False Rejection Rate

HiG Gjøvik University College

IEC International Electrotechnical Commission

IEEE Institute of Electrical and Electronics Engineers

ISO International Organization for Standardization

NTNU Norwegian University of Science and Technology

NIST National Institute of Standards and Technology

RFC Request For Comments

ROC Receiver Operating Characteristics

TER Total Error Rate (FMR + FNMR)

WMA Weighted Moving Average

Chapter 2

Authentication and Biometrics

Biometric technology is a rapidly evolving field with applications ranging from accessing ones computer to obtaining visa for international travel. The deployment of large-scale biometric systems in both commercial (e.g. Disney World [28], airports [14]) and government (e.g. US-VISIT [46], *Altinn* [38, 5]) applications has served to increase the public awareness of this technology. This rapid growth in biometric system deployment has clearly highlighted the challenges associated in designing and integrating these systems.

This chapter provides an overview of biometrics, and the main service provided by biometric technology: authentication. Examples of biometric traits will be included, while gait is left for the proceeding chapters.

2.1 Authentication and Identification

Two services are particularly important in the field of biometrics: identification and authentication. These are two closely related concepts, both essentially mean to establish the identity of an individual. However, in a security context the distinction between the two is vital. Identification means to determine the identity of a person without any bias - he or she could be *anyone*. When identifying that someone we are simply trying to answer the question ”who is this person?”. On the other hand, authentication means to *verify* an identity, answering the question ”is this person who we think?” or ”is this person who he claims?”.

The distinction is important for many reasons, but the most commonly given reason is the difference in security strength. Imagine that there are N people registered in a database, and Bob wants to log in. If the system **only** uses, say, a biometric identifier from Bob (e.g. his face) for identification, up to N comparisons are necessary in total. That also implies N chances for a false accept! On the other hand, if Bob also provides his user name, and the system looks it up to find the correct biometric trait, only one comparison is necessary. This example also shows how performance differ in the two cases - authentication requires much less computational power.

In this report, the term authentication will be used more frequently than identification. However, a lot of the theory applies to both of these services, for instance the three identity establishment mechanisms described shortly.

So how do we establish, or determine, an identity? There are three fundamental categories of how to perform this task, often cited in scientific literature [52, 29, 38]. In essence, all approaches for human recognition rely on at least one of the following:

- Something you know (knowledge)
- Something you have (possession)
- Something you are (characteristic)

The following three subsections will briefly describe each category. It is also worth mentioning that many authentication systems take advantage of several of these simultaneously, for instance by using a biometric identifier in addition to a password (characteristic + knowledge).

2.1.1 Knowledge-Based Authentication

A secret is the most commonly used key to authentication, passwords being the most intuitive example. We use passwords for web sites, online banks and e-mail accounts, and similarly PIN codes for ATMs and cell phones. Network and telecommunication systems heavily rely on secrets [44, 17] and classical cryptographic systems have always been based on secrets [52]. There are good reasons for using knowledge-based authentication; especially its cheapness and intuitiveness. Implementation is usually easy and result in very efficient and fast systems.

So that is the bright side, let us look at some of the less fortunate properties of knowledge-based authentication. Traditionally security and usability are not best friends. A secret must be remembered, and the average user prefers having an easy password - having to remember difficult character strings is a burden. Stallings presents some interesting studies in [52] where user password selection is the topic. Results show that a vast number of users select extremely short passwords when allowed to do so, and many other passwords are whole dictionary words, names of places, celebrities, cartoons, movies or similar easily guessable words. Hence, dictionary attacks are extremely efficient against the average user, that is, if no constraints are present.

There are many ways to fight these problems, interesting approaches can be found in [50, 52]. A common approach is to let passwords expire, but users tend only to change minor parts of an expired password, or add predictable phrases like the current month or day of the week. Computer-generated pass phrases are also common today, but are likely to annoy the user and give him an incentive to write it down physically.

Despite these challenges, knowledge-based authentication remains the most commonly used services today, and there is no reason for the trend to change in the immediate future.

2.1.2 Possession-Based Authentication

Today many institutions with a high incentive to protect their members or customers (e.g. banks) provide some sort of physical object, a possession, for authentication. An example is the *BankID* used by several companies in both the public and private sector in Norway and other European countries [7]. In essence the device is a Pseudo-Random Number Generator (PRNG) based on a seed known only to the issuer. The user provides a number as a one-time password to authenticate, and the third party will assume that if the number is correct, the subject is legitimate because he is in possession of the generator. Other examples of authenticating possessions are are SIM cards, smart cards, tokens, ATM cards, credit cards and keys.

Disadvantages with this scheme do exist, first of all it is more expensive than other authentication mechanisms. Producing, managing, issuing and revoking such items adds significant operational costs for the company or issuer. It is also not necessarily secure; the possessions can surely be stolen and in some cases replicated.

2.1.3 Characteristic-Based Authentication

A characteristic exhibited by someone essentially means a biometric feature belonging to that person. This form of authentication is based on the way we recognize each other in the physical world. In computer science we have to narrow down the authentication to simple pattern recognition [34], but the technology is evolving rapidly. Examples of biometrics are shown in Figure 2.1, and we often classify different biometric trait into two categories, which may also overlap:

- Physiological biometrics
- Behavioral biometrics

Physiological biometrics are characteristics that you cannot alter easily, they are stable parts or properties of your body. Examples are fingerprints, DNA, iris and retina. Behavioral characteristics can be altered and learned, such as gait, signature and keystroke dynamics. An interesting thing to note is that even though these two categories have similar vulnerabilities, they are subject to very different forms of attacks. This will become clear in the proceeding sections.

2.2 Biometrics in General

Biometrics is the study of using intrinsic biological traits to uniquely identify individuals [34]. For humans, identifying individuals is an apparently simple intuitive process that engages the entirety of the perceptory system, and applies mental processes which are not fully understood. Within computer science, biometrics is often considered to be within the field of pattern recognition, and creating automated system approaches to such has been challenging [34].

Researchers became interested in biometrics centuries ago, so the science itself is far from new. Valuable references to historical as well as modern research are found in [34], where Ross et al. have also published extensive material from their own research. The book covers various kinds of biometric traits (see Figure 2.1) such as iris, voice, fingerprint, hand geometry, DNA, gait, ear, palm print and others. The book gives a good picture of what is feasible to use as biometric identifiers today, and what might be feasible in near future.

A biometric trait must meet certain requirements before it can be considered an identifier. Evaluation of how specific biometrics satisfy these can be found in [27, 62, 34]. The results agree in general that traits that have been subject to research for a long period of time, like the fingerprint and iris, indeed exhibit the most important properties.

Important evaluation criteria for biometric traits are often summed up like this [38]:

- Universality - ”everyone” should possess the identifier.
- Uniqueness - the identifier should be able to differentiate one individual from every other.
- Permanence - the identifier should be reasonably stable over time.
- Collectability - collecting the biometric data must be technically possible, and not too intrusive or inconvenient.
- Performance - the speed and accuracy of recognition in a biometric system should be acceptable when using the identifier.
- Acceptability - use of the identifier should be accepted by the public.
- Circumvention - biometric systems based on the identifier should be secure (e.g. against forging).

All traits have weaknesses, so a strict requirement on every single one of these criteria is not what we want. Even if fingerprints are universal, some people are not suited for the biometric due to diseases or missing limbs [38].

The four first criteria can be seen as the most interesting ones in the context of this thesis, mainly because the latter three are more related to biometric system design. Interesting discussion on this topic can be found in various literature, for instance by Pankanti and Yoon et al. [57, 62]. A comparison of different biometrics is presented in the end of this chapter.

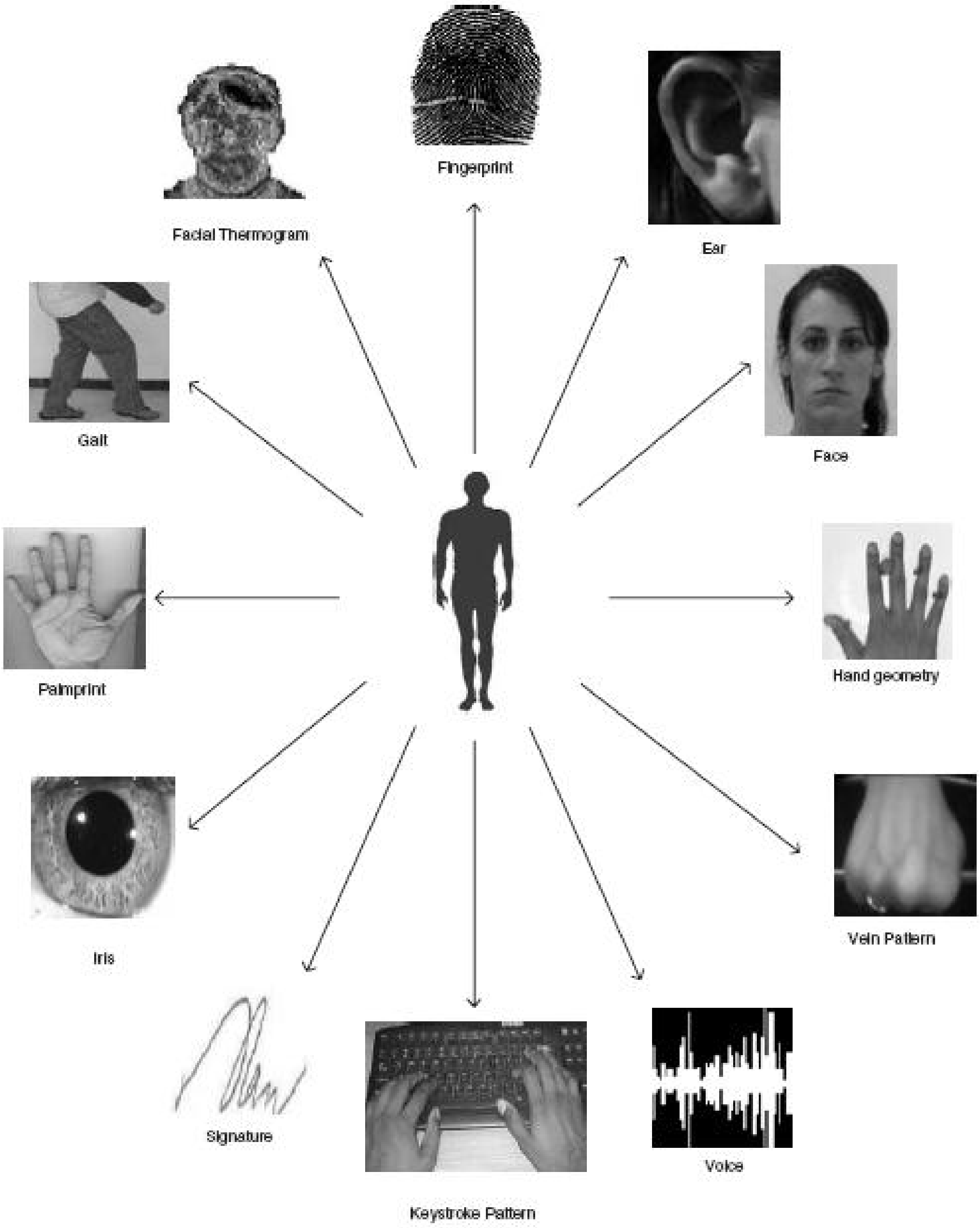


Figure 2.1: Examples of biometrics that could be used for identification [34].

2.2.1 Physiological Biometrics

Physiological biometrics consist of characteristics that you normally cannot alter, they are stable parts or properties of your body. Acquisition of biometrics in this category requires users to be active, in essence to perform some activity in front of a sensor. Examples are fingerprints, DNA, iris, retina, face, hand geometry and ear.

The most classic example of this category is the fingerprint. A fingerprint is the representation of the epidermis of a finger: it consists of a pattern of interleaved ridges and valleys. Much research has been done on the trait; for example on uniqueness [27, 34], processing [30, 31, 55] and use in authentication systems [32].

The fingerprint biometric technology is considered a lot more mature than what exists for many other identifiers, and the feature is considered to exhibit the most important characteristics mentioned in Section 2.2 [38]. Despite this, threats towards fingerprints do exist, for instance template reconstruction [12], synthetic fingerprint generation [34] and silicone finger forging [42].

2.2.2 Behavioral Biometrics

Behavioral biometrics are properties of a person that can be altered and sometimes learned, it is about what a person *does* rather than *is*. In this category, acquisition of the trait does not require an active effort by the user, and sometimes not even the user's cooperation. Hence, behavioral biometrics han be acquired even without explicit consent of subjects.

Gait biometrics is an obvious example, and constitutes the topic of this thesis. For completeness the reader may consider a second example: keystroke dynamics.

Already during World War II telegraph operators could recognize the sending operator by his typical keying rhythm (of Morse-code). Keystroke dynamics is the process of analyzing the way a person types at a keyboard and identifying him based on this [9].

Typical uses for this biometric is in the context of a password entry. Instead of only validating a user's password or PIN code, this can be checked by fusion - combining the entered data with the dynamics of the typing, providing joint security.

When looking at keystroke dynamics, we are interested in latency (time delay between button release and depression of the next), the time each key is being held down, the pressure applied to the keys, finger placement and finger choice [9]. Patterns generated from these characteristics can be used to recognize individuals [40, 34].

Other keystroke related biometrics exist, as well as attacks using such biometrics. One particular attack on keystroke acoustics can be found in [63]. In this article an approach to retrieving a password from a user based on the sound of his typing is described.

2.3 Biometric System Design

Despite the numerous different biometrics that have been suggested, the designed systems are conceptually very similar. They can all be viewed essentially as pattern-recognition systems and usually consist of four distinct loosely-coupled parts [33, 55].

Sensor The sensor obtains a sample of the biometric trait, such as a signature or the picture of a fingerprint or a face.

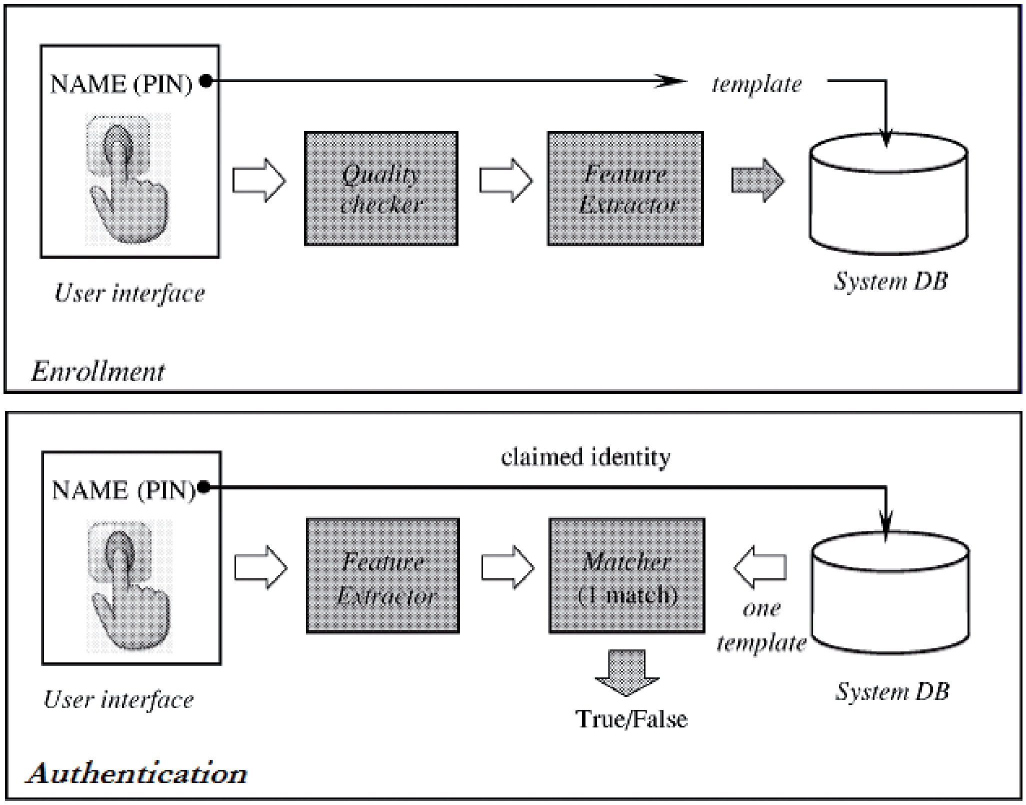


Figure 2.2: A biometric authentication system during enrollment (top) and authentication (bottom) [29].

Feature Extractor The feature extractor extracts the important characteristics from the raw biometric signal stream. Traditionally for verification and identification systems, the result of this extraction is a biometric template.

Database The database stores the results from feature extraction, like templates. Recently, templates have been subject to a lot of research, and it has been claimed that far too much information is revealed from them [34, 55, 12, 38].

Matcher The matcher component traditionally compares two biometric templates, and attempts to determine whether the templates represent the same individual.

A conceptual figure illustrating the parts above can be seen in Figure 2.2.

2.4 Attacks on Biometric Systems

To understand the threats against biometric systems, it is valuable to look at the different points of attack. Ratha et. al defined eight such points in [47], illustrated by Figure 2.3. These points are described as follows:

1. Presenting fake or imitated biometrics to the scanner or collector.

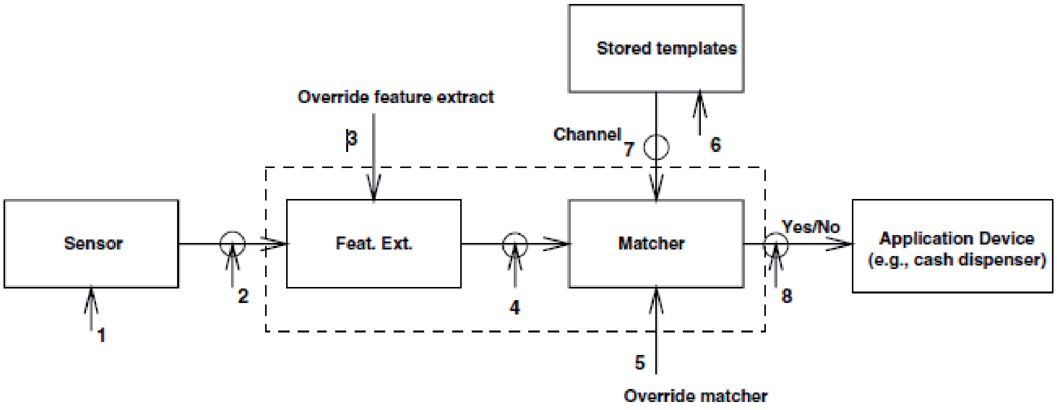


Figure 2.3: Eight attack points in biometric authentication systems [47].

2. Re-submitting previous samples or altering transmitted samples.
3. Attacking the feature extractor so that it produces attacker dictated values.
4. Substituting extracted feature values with values dictated by the attacker.
5. Manipulating the matcher so that a desired score is produced.
6. Manipulating the template database.
7. Attacking the transmission channel between the database and the matcher.
8. Manipulating the decicion produced by the system as a whole.

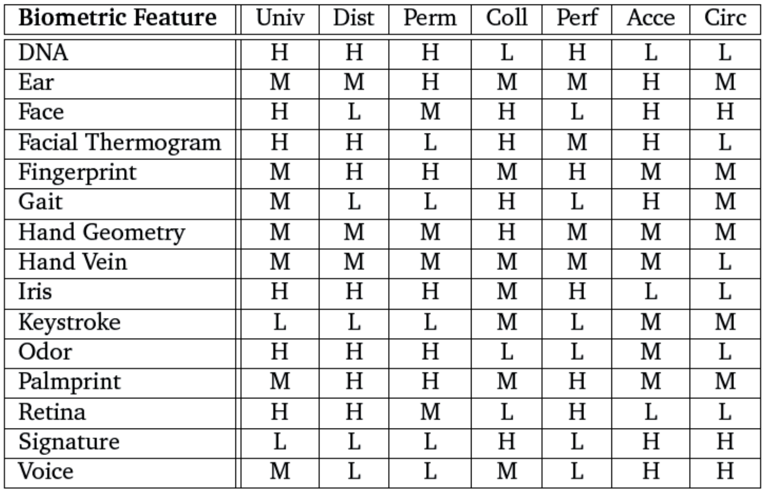
This thesis will concentrate on mimicking, which corresponds to attack point one. The reader should keep in mind that this is only one of many approaches to attacking a biometric system, but it should also be noted that this is the most intuitive one for gait biometrics. Anyone can perform an imitation attack without any knowledge of computer science.

2.4.1 Comparing Biometric Traits

Based on the characteristics from Section 2.2, Jain et al. have compared several biometrics in a study from 2004 [29], summarized in Table 2.1. However, it is not trivial to say which is better than the other because different systems call for different needs. It is also important to remember that scores shown here could be altered as technology improves. For instance, gait does not appear to do well in Jain's study, but the technology evolved around gait is hardly mature at the time of writing, and much less back when his study was conducted.

2.5 Errors

The quality of a biometric system is measured by error rates. Obviously, we want the system to function as well as possible, the fewer errors the better. Since



Biometric Feature	Univ	Dist	Perm	Coll	Perf	Acce	Circ
DNA	H	H	H	L	H	L	L
Ear	M	M	H	M	M	H	M
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

Table 2.1: Comparison of various biometrics [29]. High, medium and low denoted by H, M and L, respectively.

biometrics are analyzed by taking samples, a biometric system is never perfect. A knowledge- or possession-based authentication system does not experience the same problems - a character string does not change.

So, what kind of errors are we interested in? Mainly, we wish to look at the False Match Rate (FMR), and the False Non-Match Rate (FNMR) [2, 38] [1]. The FMR tells us how often a person is mistaken for being someone else, for instance when an impostor is mistaken for a legitimate user, and the FNMR tells us how often a legitimate user is wrongfully rejected. These rates can be calculated quite intuitively [29]:

$$FMR = \frac{\text{Number of impostor accepts}}{\text{Number of impostor tries}} \tag{2.1}$$

$$FNMR = \frac{\text{Number of client rejects}}{\text{Number of client tries}} \tag{2.2}$$

When comparing a biometric sample to a stored template, two ways to determine its correctness are common. One is to use a distance metric, where a lower value means less ”distance” between two samples (high correctness). We want a low intra-class distance metric, which means that two samples from the same person should be pretty much equal, while the inter-class distance metric should be high, because it is based on samples from different persons. The second way of measuring is a match score, where the exact opposite is desired - high match score means high level of correctness. Essentially these two methods are the same, and there are many specific methods on how to actually compute them. This will become clear in Section 3.3.6.

[1] A term that will only be used in this introduction is False Acceptance Rate (FAR). The same applies to False Rejection Rate (FRR). These are somewhat different from FMR and FNMR, as FAR and FRR also include rates like Failure to Capture (FTC) and Failure to Enroll (FTE).

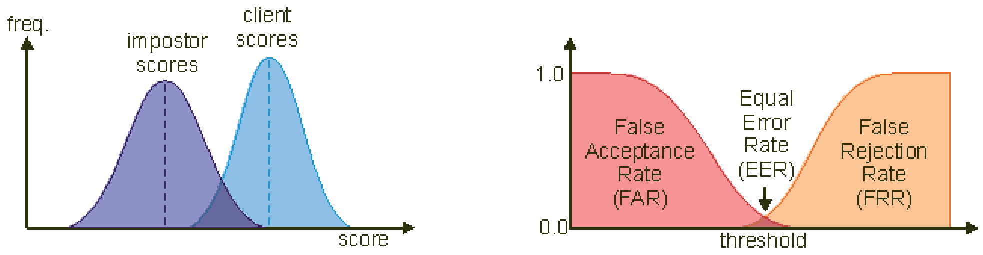


Figure 2.4: Error rates in biometric systems. Left: An enrolled client has a distribution of match scores shown by the taller bell-shaped curve, while an impostor is represented by the shorter curve. An overlap is present in this example, meaning the two sometimes might get scores in the same range. Right: A threshold of strictness on the x-axis. High strictness means many false rejects, and vica versa. The point where FAR = FRR (somewhat similar to FMR = FNMR) is the EER [2].

Obviously, we need a threshold to determine what is a match and what is not. Figure 2.4 shows a representation of the concepts. The left figure shows the score distribution of a legitimate user and an impostor. The right figure shows the FAR and FRR relative to a threshold of strictness. The point where the FAR and FRR are the same, is known as the Equal Error Rate (EER). This is often used for measuring the quality of service in biometric systems, and obviously we want it as low as possible [34].

The tradeoff between FMR and FNMR is also important because changing the threshold may give unequal changes in the two rates. Two commonly used tools are the Receiver Operating Characteristics (ROC) curve, and the Decision Error Tradeoff (DET) curve [29]. Only the DET curve will be used in this thesis, Figure 2.5 provides a conceptual illustration.

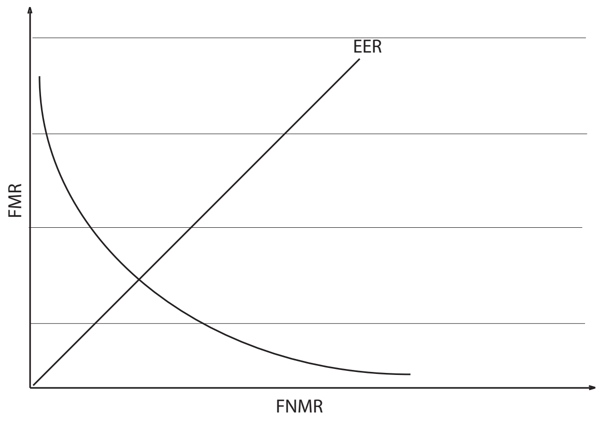


Figure 2.5: Decicion Error Tradeoff (DET) curve.

The DET curve shows system performance in terms at different thresholds, and the FMR / FNMR tradeoff related to it. The DET and ROC curves are used for the same general purpose, and their differences mainly consist of the values and meaning of the axises [29]. The reader should keep in mind that thresholds are very dependent on the system at hand, and these examples are only conceptual illustrations.

Finally, two other types of errors are common - failure to enroll and capture. Their corresponding error rates are called Failure to Enroll Rate (FER) and Failure to Capture Rate (FCR) [29]. These are less interesting to the thesis, since it will be discussing properties of the gait itself. These two rates would be much more interesting in a context of competing hardware or biometric system design, and will not be discussed further.

Chapter 3

State of the Art

This chapter will introduce previous work on gait biometrics and challenges related to gait recognition technology. The reader will be brought up to date with the current state of the art, and the thesis is positioned relative to previous research to clarify the intended contribution.

3.1 The Gait Biometric

The gait of a person is a periodic activity with each gait cycle covering two strides - the left foot forward and the right foot forward. It can also be split up into repetitive phases and tasks as illustrated in Figure 3.1.

Potential sources for gait biometrics can intuitively be categorized into *shape* and *dynamics* [34]. Shape refers to the silhouette or configuration of certain parts of the body during different phases of the gait cycle, while dynamics refers to such as the rate of transition between the phases, acceleration and similar motion related characteristics.

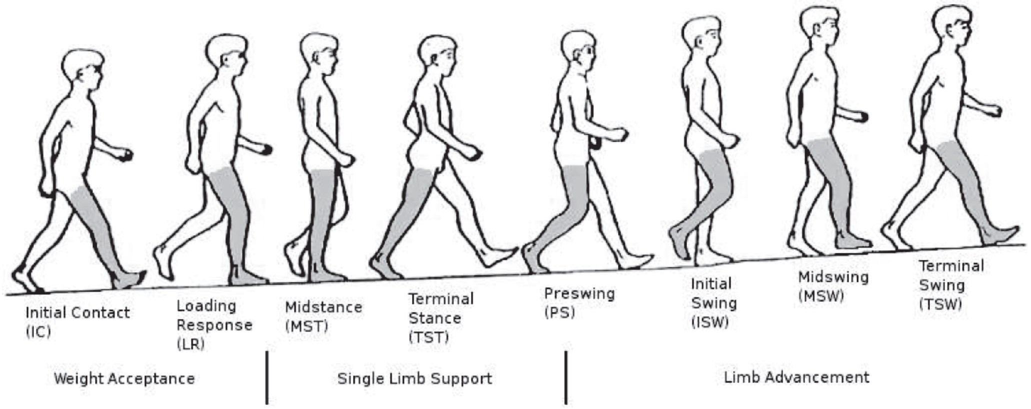


Figure 3.1: The complete gait cycle showing its three tasks and eight phases [43].

3.2 Gait Collection and Recognition

Gait recognition has intrigued researchers for some time, already in the 1970's there were experiments done on the human perception of gait [34]. The first effort towards automated gait recognition (using machine vision) was probably done by Niyogi and Adelson [45] in the early 1990's. Several methods are known today, and we can categorize all known gait capturing methods into three categories [19]:

- Machine Vision based (MV)
- Floor Sensor based (FS)
- Wearable Sensor based (WS)

The experiment in this thesis uses accelerometers to collect gait. Hence, the WS category is the one of interest in this case, but also the first two methods will be shortly discussed for the sake of completeness.

3.2.1 Machine Vision

Machine vision was the main focus of gait biometrics in the earlier stages [34], and utilize the shape characteristic of the human gait. Most of the MV-based gait recognition systems are based on the human silhouette [19]. That is, the background is removed and the silhouette is analysed for recognition as seen in Figure 3.2. Many approaches to the analysis are possible. One is to compute the average silhouette over an entire gait cycle. Such methods face some challenges if the video background is not known and adjusted in advance of the video capturing. MV-based gait recognition systems have shown good results in performance, and most systems using the gait biometric today is MV-based, and recognition rates up to 95% has been reported [19]. The scheme solves the problem described in the introduction to the thesis, how to identify someone when the distance is too large for using physiological biometrics.

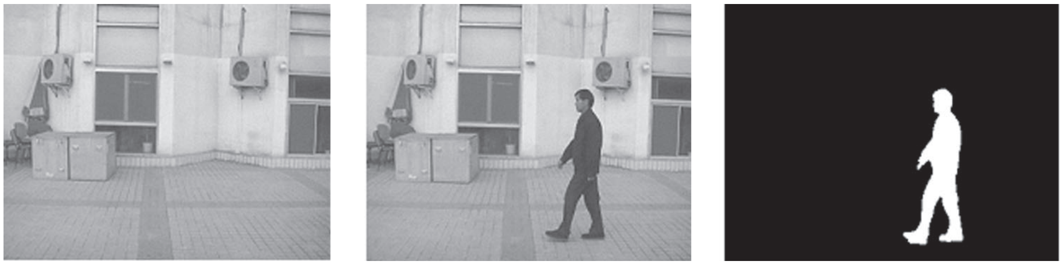


Figure 3.2: Using the human silhouette for gait recognition [60].

3.2.2 Floor Sensors

Floor sensors can be installed in floors or carpet-like objects (see Figure 3.3, and are able to measure gait related features when walked upon. This will result in footstep profiles that can be based on positioning, or the timing between heel vs toe strikes etc. A summary of findings for this category is found in [19] by Gafurov, where he reports recognition rates spanning from 70.2% to 93% for several different methods.

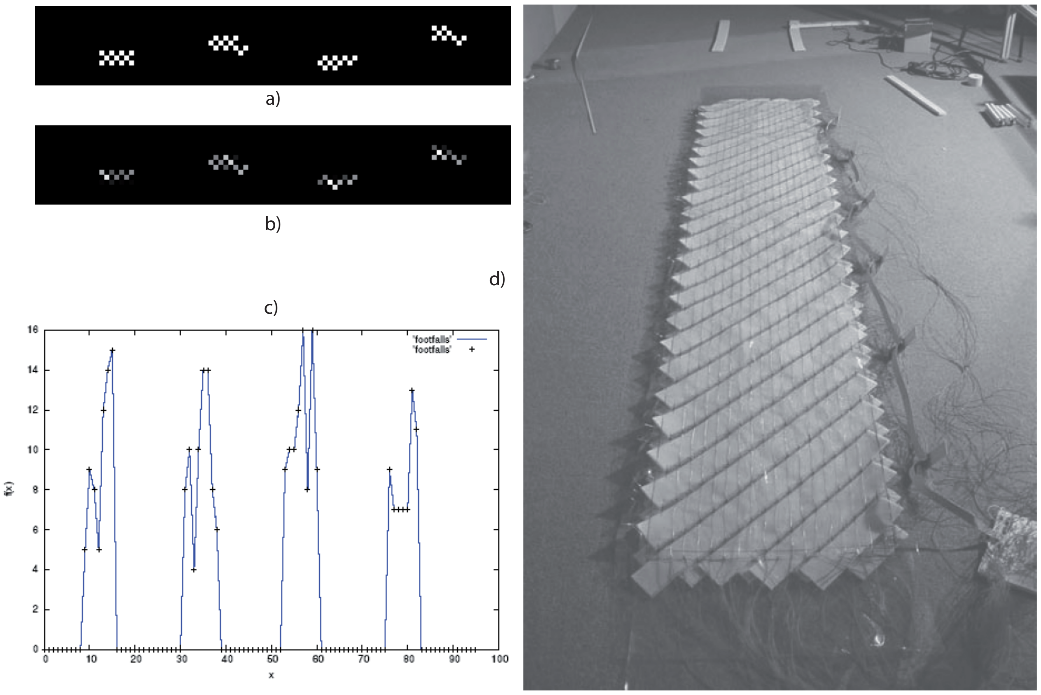


Figure 3.3: Gait collection by floor sensors. a) shows foot steps recognized, b) shows the time spent at each location in a), c) shows footstep profiles for heel and toe strikes, and finally d) is a picture of a prototype floor sensor carpet [19, 29].

One of the main advantages with this scheme is in its unobtrusive data collection. Sensor carpets can be placed in front of doors or in hallways, and can also provide location information within a building [19].

3.2.3 Wearable Sensors

Using wearable motion recording sensors to collect gait data is a rather newly explored field within gait biometrics. The earliest description of the idea known to the author is found in Morris' [41] PhD thesis from Harvard University in 2004. Since then, the academic community at Gjøvik University College (HiG) has devoted much effort researching gait biometrics. Gafurov's PhD work covers a broad part of WS-based gait recognition [18, 19, 21, 22, 23, 24, 25, 26], and several students have written their master's thesis on the same topic [53, 29, 43, 11].

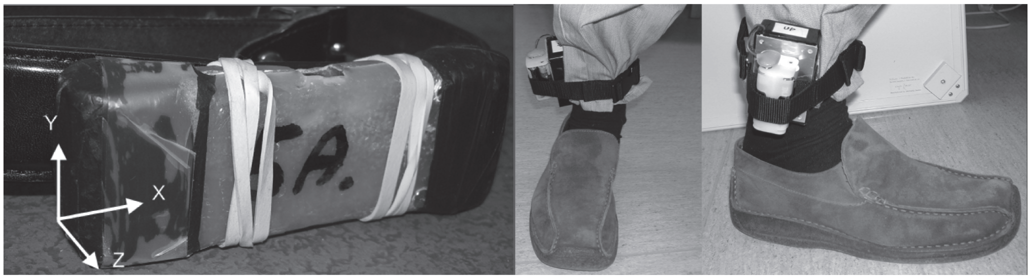


Figure 3.4: Wearable sensor equipment from earlier experiments. Left: Gait collector attached to a person's belt [29]. Right: Gait collector attached to a person's leg [43].

The sensors can be worn on different parts of the human body, such as hip and ancle. Error and recognition rates may vary accordingly, and results also vary based upon the chosen analysis methods, technology and experiment design. Comparison attempts will be presented shortly.

In [21] Gafurov et al. used ankle-attached sensors and achieved EERs of 5% and 9% by utilizing the *histogram similarity* and *cycle length method*, respectively. These methods were also applied when attaching sensors to the hip, and an EER of 18% was achieved [11]. This result was vastly improved by Holien by fine-tuning the cycle detection and other subtasks of Gafurov's algorithms; an EER of 2% was achieved for normal walk [29].

WS-based gait collection has the advantage of being a rather unobtrusive way of collecting biometric data. It also opens up for a wide range of applications - imagine a mobile device recognizing its owner, locing down for PIN-authentication if an unknown gait is detected. If mobile devices, such as cell phones, become extensively used in such as mobile commerce and banking, this security mechanism could be very valueable. People are not too careful with their cell phones today, according to UK statistics, a mobile phone is stolen approximately every three minutes [19]. If cell phones in addition becomes a person's wallet, the constant verification of gait certainly constitutes a good candidate for an additional protection mechanism.

3.2.4 Comparison of Gait Collection Methods

Table 3.1 summarizes the findings of much research, utilizing different hardware and software methods, with different number of test subjects and quite different results. For comparison, Table 3.5 shows the performance achieved by some other biometric traits.

The table is intended to give an overview of research, but the test data and environment are so different that it is by no means meant to provide a direct comparison.

FS and WS have the immense advantage over MV of avoiding external noise factors such as camera placement and background or lighting issues. MV is an expensive

Study	S	EER, %	Catg.
BenAbdelkader et al. [24]	17	11	MV
Wang et al. [24]	20	8, 12, 14	MV
Wagg and Nixon [24]	115	64, 84	MV
Orr and Abowd [24]	15	93	FS
Suutala and Roning [24]	11	65.8-70.2	FS
Middleton et al. [24]	15	80	FS
Ailisto et al. [4]	36	6.4	WS
Mantyjarvi et al. [3]	36	7, 10, 18, 19	WS
Gafurov et al. [21]	21	5, 9	WS
Gafurov et al. [26]	22	16	WS
Gafurov et al. [24]	50	7.3, 9.2, 14, 20	WS
Gafurov et al. [25]	100	13	WS
Rong et al. [48]	35	6.7	WS
Holien [29]	60	2	WS
This research	50	6.2	WS

Table 3.1: Performance overview of several gait recognition approaches. S, EER and Catg. represents the number of test subjects, EER performance and category, respectively. The categories MV, FS and WS corresponds to Machine Vision, Floor Sensors and Wearable Sensors, respectively.

solution in terms of camera equipment, covering an area with floor sensors is not cheap either. The WS do not require any infrastructure in the surroundings, and is mobile, this is another huge advantage over the other two solutions. In terms of unobtrusiveness, both FS and WS are considerably better than MV [4, 37].

So far, MV and FS has mainly been used for identification, while WS has been used for authentication [29], this is rather intuitive considering the nature of the three approaches.

In this thesis, only the WS will be considered. This is mainly due to the advantages listed above, in addition to the expertise and equipment that was available at HiG at the time of writing. Some more discussion is found in Section 4.2.

3.3 Gait Acceleration Data

The wearable sensors (WS) uses accelerometers to collect acceleration data in the X, Y and Z direction, but there are many ways to go from there. Several methods have been tested, with varying results, and some of these will be presented here.

Figure 3.5 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. Another example is seen in Figure 3.13. Gafurov reports in [21] that using a combined signal has the advantage of making the scheme less sensitive to the random noise.

Gafurov et al. refers to many different methods of combining the signals, but states that the best performance is achieved when using all three dimensions combined

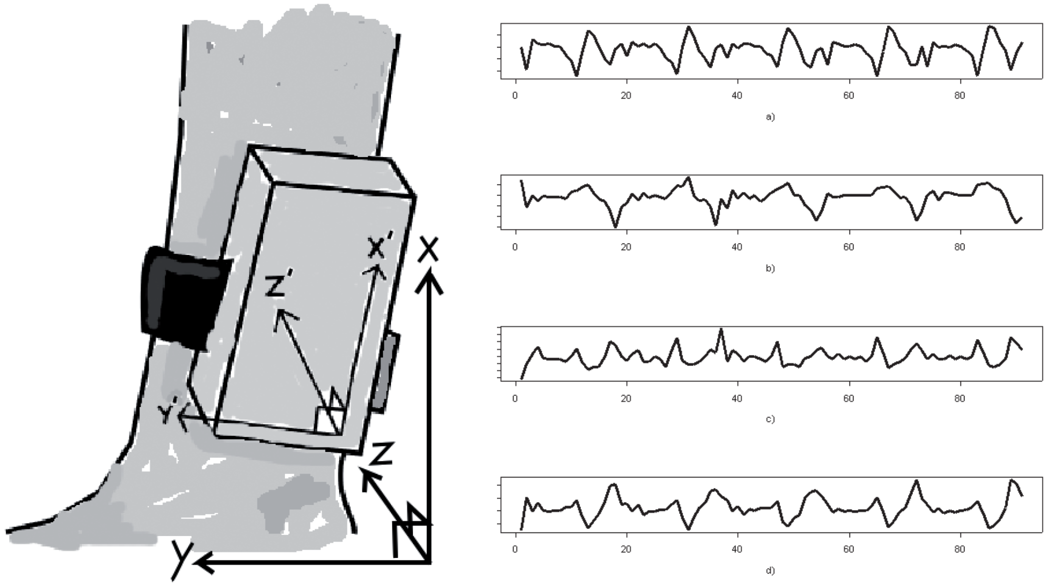


Figure 3.5: Gait acceleration graphs and directions. a) Vertical X, b) horizontal Y and c) sideways Z. The bottom graph, d), is a combination of a), b) and c), the resultant. The left figure shows an accelerometer attached to a leg, with directions indicated. [21]

into a resultant. Gafurov ends up using [21, 24]:

$$r_i = \sqrt{X_i^2 + Y_i^2 + Z_i^2}, i = 1, \ldots, k \tag{3.1}$$

where k is the number of recorded samples, and X_i, Y_i, Z_i, is sample i in direction X, Y and Z, respectively.

3.3.1 The Cycle Length Method

The cycle length methods was designed by Gafurov [21]. In essence, it is simply a framework on how to take a gait sequence and turn it into an averaged gait cycle of fixed length. When the average cycle is computed, comparison can take place using distance metrics or similar tools described in Section 3.3.6.

The method is based on averaging gait cycle *groups*. This term will not be used beyond this chapter, but in essence Gafurov uses the groups to create an average gait cycle.

Cycles are identified by looking at the vertical acceleration signal [21]. A zero value is found by looking at a negative value followed by a positive value, after also scaling the data by subtracting the mean from every value. Other zero points are detected relative to this zero value, using the cycle length which can be calculated from the autocorrelation function. This way the entire sequence is divided into gait cycles. Note that these may or may not be the actual cycles of the gait, it does not matter for the processing.

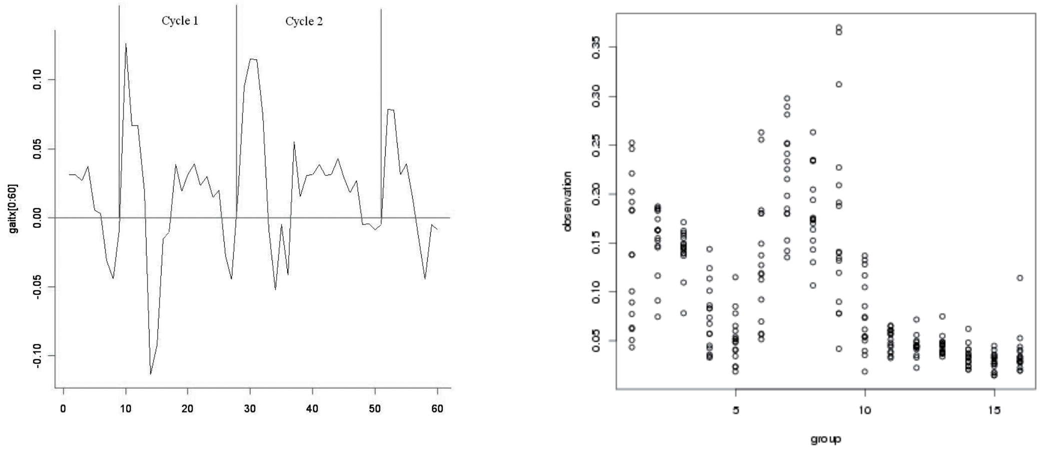


Figure 3.6: Cycles (left) and cycle groups (right) [21].

Once the cycles have been identified, the acceleration samples can be divided into groups. Then number of such groups varies with the length of the cycle, and the number of samples per unit of time. In [21], only 16 groups are made because only the first 16 out of 22 samples are used for comparison. This is represented in the right part of Figure 3.6.

The final task is to perform the group comparison. There are many ways of doing this, one intuitive solution is to compute the mean or median of each group, to create an average gait cycle. In [21], the mean is used together with a statistical t-test. This can be a little problematic if the acceleration samples contain many extreme values. In an ideal scenario with gait frequency and pattern being essentially constant, the mean value would be a very good choice because the cycle groups would be normally distributed.

The final output is the average gait cycle of a fixed length, which can be considered the template of a person's gait.

3.3.2 Ailisto's Gait Cycle Method

This method was developed by Ailisto et al. and is used in some of the first publications on WS-based gait recognition [4, 3, 37]. The approach is very similar to that of Gafurov, presented in Section 3.3.1. The method consists of finding individual steps, normalizing and averaging them, aligning them with a previously generated template and generate cross-correlation values. An EER of 6.4% was achieved this way [4]. The target output is still an average gait cycle, though in the case of Ailisto it is constructed a bit diferently. Figure 3.7 provides an illustration, where the *step pair* is equivalent to Gafurov's cycle, while each of two individual steps are analyzed separately in Ailisto's method.

In other words, the gait cycle from Gafurov is split in two parts in this method. Table 3.2 describes the algorithm concept - both "a-steps" and "b-steps" are averaged and

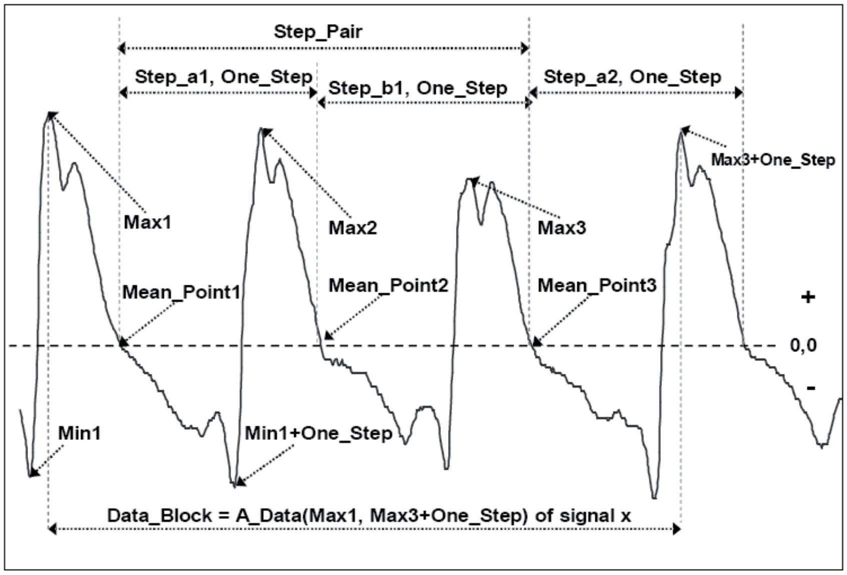


Figure 3.7: Ailisto's gait cycle signal [4]. Notice that one cycle constitutes one step or stride.

included in the template. It does not matter which one is left and which one is right, upon verification both configurations are tested and only the maximum similarity (cross-correlation, C in Ailisto's algorithm) is considered. The comparison lies outside of Ailisto's method, but it is included here the same way as in [4].

Again, the output is average gait cycles, and several tools can be used to compare this template to other cycles (distance metrics in Section 3.3.6).

Enrollment
1. Divide the signal to parts representing steps.
2. Normalize the parts, so that their amplitudes and lengths are equal.
3. Average "a-steps" and "b-steps" of signals x and z forming the gait code [xa xb za zb].
Authentication phase
4. Repeat steps 1-3 for the sample c and d steps, resulting in the gait code [xc xd zc zd],
5. C = Max({c(xa,xc) + c(xb,xd) + c(za,zc) + c(zb,zd)}, {c(xb,xc) + c(xa,xd) + c(zb,zc) + c(za,zd)}), where c() is correlation.
6. If C > T (threshold), then accept, else reject

Table 3.2: Ailisto's gait recognition algorithm [4]. Note that the particular left and right stride does not have to be determined, because the method will check similarity with both configurations and keep the higher score.

3.3.3 The Fast Fourier Transform Method

Instead of looking at amplitudes of the gait signal in the time domain, we can look at the frequency domain. For this task we use a well known mathematical tool: the Fourier transform [36]. Gafurov did this when experimenting with the arm swing as a (weak) biometric identifier [22]. In this paper, the arm swing signals were treated as a whole, quite contrary to the methods presented in Section 3.3.1 and 3.3.2.

Generalizing from [22] we obtain the FFT method. After a pre-processing step, basically consisting of interpolation of the acceleration data, the following equation transforms the signal to the frequency domain [36, 22]:

$$r(t) = a_0 + \sum^{k} [b_i \cdot \sin(2\pi f_i t) + c_i \cdot \cos(2\pi f_i t)], \tag{3.2}$$

where the values a_0, b_i and c_i are known as the Fourier coefficients. These are computed using the FFT algorithm, and enables us to compute the amplitude of the signal at every frequency:

$$A_i = \sqrt{b_i^2 + c_i^2} \tag{3.3}$$

The arm swing signal from [22], and its corresponding frequencies can be seen in Figure 3.8.

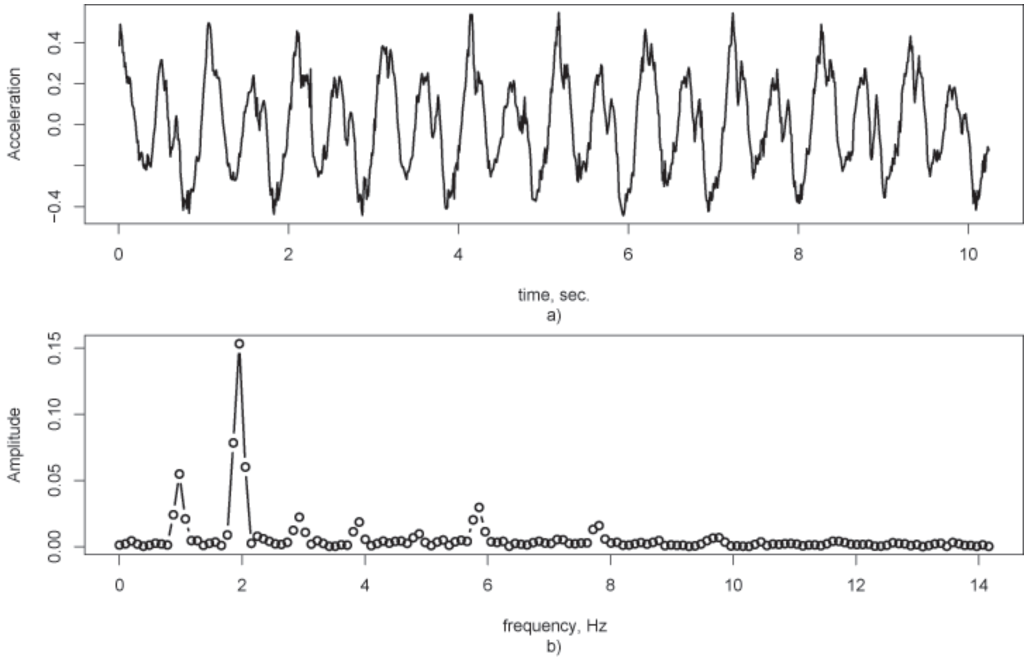


Figure 3.8: Arm swing signal in time (a) and frequency (b) domain [22].

Once the transform is complete, we can derive features from the signal in order to create a template. This can also be done in several ways, in [22] the frequency axis is divided into ranges, and the highest amplitude within each range is used as the features, concatenated in a feature vector.

Finally, similarity scores are calculated between the feature vector and a sample for verification. Again several different metrics can be used, Gafurov selected the Euclidean distance metric one of his FFT experiments (equation 3.6). In this experiment several templates were tested, differing only in the number of features, and the best EER achieved was 10% with 6 features [22]. From this it seems that the current state of FFT technology is inferior in the context of gait biometrics, and the thesis will not look at it any further.

3.3.4 Dynamic Time Warping

Dynamic Time Warping (DTW) has numerous applications in science, in the context of gait biometrics it can be used as a distance metric [35, 49] or a tool for finding median cycles [29]. In this thesis, DTW will be used for the former purpose - to determine separability between gait cycles.

In comparison to the other distance metrics, which are presented in Section 3.3.6, DTW will be discussed here in a separate subsection. This is mainly due to the amount of theory being presented, and to stress that the method can also be used in other areas within gait biometrics.

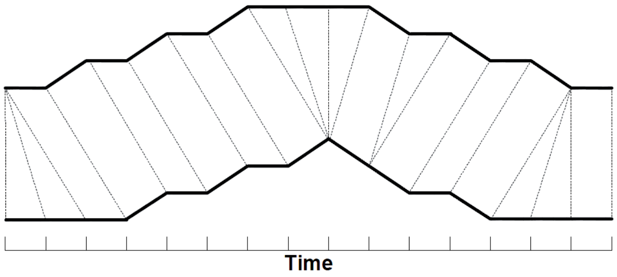


Figure 3.9: Dynamic Time Warping (DTW) [49]. A warping between two time series.

The description presented here is mainly based on the classic DTW method, and is more extensively described in [35, 49]. The main purpose of DTW is to identify an optimal way of transforming a sequence into another, as illustrated by Figure 3.9. The name comes from the idea that one sequence might originate from another, but is not identical to it because it has been ”warped” non-linearly by stretching or shrinking.

DTW is almost identical to the *Levenshtein* distance, which again is also known as *edit* distance. The latter two terms will not be used in this thesis, we will only refer to ”DTW distance”.

DTW Operations

Suppose we have two strings, ”Saturday” and ”Sunday”, which are of the unequal lengths of eight and six characters, respectively. We need to determine different ways of transforming one of these into the other, and we have three available tools. The tools are:

- **Insertion** is the operation of adding a character somewhere in a sequence. The cost of this operation will be represented by $\mathcal{C}_{ins}(x)$, where x is the inserted character. This cost could be fixed, or depending on the character value.

- **Deletion** is the operation of removing a character somewhere from a sequence. The cost of this operation will be represented by $\mathcal{C}_{del}(x)$, where x is the deleted character. This cost could be fixed, or depending on the character value.

- **Substitution** is the operation of replacing a character with another. The cost of this operation will be represented by $\mathcal{C}_{sub}(x, y)$, where x is the original character to be substituted by y. To calculate the cost of this, a distance metric can determine the separability between the two characters. The absolute value of the difference is an intuitive tool, but other versions also exist, for instance using fixed costs.

The Cost Matrix

For our example sequences ”Sunday” and ”Saturday”, we construct a 9×7 matrix ($n + 1 \times m + 1$), where n and m are the lengths of the two strings. Cell (i, j) represents the cost of transforming the subsequence of length i (of n), to the subsequence of length j (of m), for instance $(4, 3)$ gives the cost of translating ”Su” into ”Sat” in our example. Table 3.3 shows the example at hand, and we can further identify the three operations insertion, deletion and substitution, as standing in a cell and moving right, down and diagonally down/right, respectively. These operations can be mirrored depending on the implementation, but in this example an ”S” is inserted when moving to the right from $(1, 1)$ to $(1, 2)$, and so on. Figure 3.10 illustrates this.

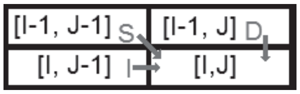


Figure 3.10: DTW operations [29]. I, D and S represent insertion, deletion and substitution, respectively. These are the three possible operations, and we are interested in comparing cost between them. It should also be noted that different implementations can result in mirroring these interpretations.

The cost of this example can be identified by looking at the underlined transformation path in Table 3.3:

$$\begin{aligned}\mathcal{C}_{tot}(Sunday, Saturday) &= \mathcal{C}_{sub}(S, S) + \mathcal{C}_{ins}(a) + \mathcal{C}_{ins}(t) + \mathcal{C}_{sub}(u, u) \\ &\quad + \mathcal{C}_{sub}(n, r) + \mathcal{C}_{sub}(d, d) + \mathcal{C}_{sub}(a, a) + \mathcal{C}_{sub}(y, y) \\ &= \mathcal{C}_{ins}(a) + \mathcal{C}_{ins}(t) + \mathcal{C}_{sub}(n, r),\end{aligned}$$

assuming that $\mathcal{C}_{sub}(\emptyset, \emptyset) = 0$. Although this example shows a character string transformation, the same methods apply to that of number sequences, or in the context of this thesis: gait cycles.

		S	**a**	**t**	**u**	**r**	**d**	**a**	**y**
	0	1	2	3	4	5	6	7	8
S	1	$\underline{0}$	$\underline{1}$	$\underline{2}$	3	4	5	6	7
u	2	1	1	2	$\underline{2}$	3	4	5	6
n	3	2	2	2	3	$\underline{3}$	4	5	6
d	4	3	3	3	3	4	$\underline{3}$	4	5
a	5	4	3	4	4	4	4	$\underline{3}$	4
y	6	5	4	4	5	5	5	4	$\underline{3}$

Table 3.3: DTW example on character strings, transforming ”Sunday” into ”Saturday”. The underlining shows the optimal transformation path.

When the cost of the transformation is calculated, we have our distance metric (in the bottom-right cell). If the cost is small, then the probability is high that the two sequences are warped versions of each other. Equivalently, if the two sequences are very different, the cost of transforming one to the other is high. This is how gait cycle distance will be calculated in this thesis, as further discussed in Section 4.3.7.

Constraints

Several constraints are imposed to ensure that the correctness of the final distance. In general DTW theory this is best described through the *warping path* $\mathcal{W}$. The warping path is a set of matrix element that defines the mapping between two sequences [35], in our example the path consists of all the underlined cells in Table 3.3. The k^{th} element of $\mathcal{W}$ is defined as $w_k = (i, j)_k$, so we have:

$$\mathcal{W} = \{w_1, w_2, \ldots, w_k, \ldots, w_K\}. \tag{3.4}$$

The following constraints apply [35, 29]:

- **Boundary condition:** $w_1 = (1, 1)$ and $w_K = (n, m)$, meaning that the warping path starts and ends in the diagonally oposite corner cells of the matrix.
- **Continuity:** Given $w_k = (a, b)$ then $w_{k-1} = (a', b')$ where $a - a' \leq 1$ and $b - b' \leq 1$. This ensures that the path between adjacent points on the warping path are restricted to adjacent cells in the cost matrix. This includes diagonally adjacent cells.
- **Monotonicity:** Given $w_k = (a, b)$ then $w_{k-1} = (a', b')$ where $a - a' \geq 0, b - b' \geq 0$ and $|a - a'| + |b - b'| \geq 1$. This forces the points on the warping path to be monotonically spaced in time.

The number of paths satisfying these constraints grows exponentially [35], but we are only interested in the optimal choice, yielding the minimum cost. This can be computed efficiently using dynamic programming, Section 4.3.7 will go into more detail on the implementation in this thesis.

3.3.5 Histogram Similarity

In the histogram similarity method we compute n bins of values 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. The method has been used in [21, 24, 4] in addition to master's thesis works [43, 11].

Figure 3.11 illustrates the process of comparing two histograms.

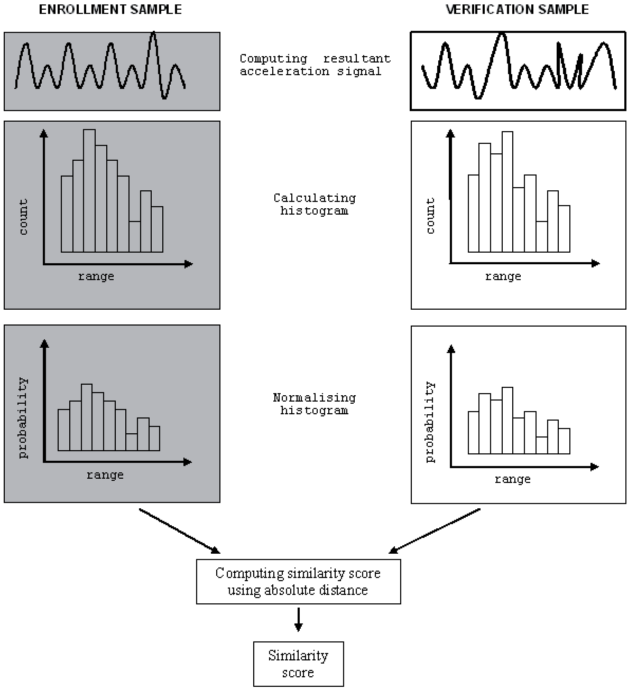


Figure 3.11: The histogram similarity method. The gait sample is converted into what represents the enrolled template histogram, while the right gait sample is being verified towards this template. [21]

3.3.6 Tools for Calculating Separability

The methods discussed in this chapter can adopt many different statistical distance metrics and similar mathematical tools to calculate a match score. It is important that the reader sees the difference between a distance metric and a similarity method or a gait cycle method. The methods described so far are complete schemes describing how to create and compare templates from gait data. Each of these methods can utilize different distance metrics when calculating differences between gait samples. It is not always easy to say which one is ”best”, because that depends a lot on the context where the metric is being used in [20].

Changing a specific metric or other mathematical tool in a method is in this thesis considered to be a *configuration* of the original method, rather than an actual new method. Since methods like the cycle length method can be configured with several different mathematical building blocks, this has simplified the structure of this chapter considerably.

Regardless of which method is used for generating templates - the following distance metrics may (and may sometimes not) be suitable for comparison with a sample for verification. In these equations, X and Y are feature vectors of length k, and x_i and y_i are samples from these vectors, respectively.

Manhattan / city block distance [61]:

$$d(X, Y) = \sum_{i=1}^{k} |x_i - y_i| \tag{3.5}$$

Euclidean distance [61]:

$$d(X, Y) = \sqrt{\sum_{i=1}^{k} |x_i - y_i|^2} \tag{3.6}$$

Chebychev distance [61]:

$$d(X, Y) = \max_{1 \leq i \leq k} |x_i - y_i| \tag{3.7}$$

Lance distance [61]:

$$d(X, Y) = \sum_{i=1}^{k} \frac{|x_i - y_i|}{|x_i| + |y_i|} \tag{3.8}$$

Divergence [61]:

$$d(X, Y) = \sum_{i=1}^{k} (x_i \ln \frac{x_i}{y_i} - x_i + y_i) \tag{3.9}$$

Like all other distances, the divergence metric has a lower bound of zero, and vanishes if and only if $X = Y$. However, this metric cannot be called a distance, because it is not symmetrical in X and Y. Hence, we call this divergence from X to Y. A symmetrized version does exist, found in [61].

Kullback-Leibler distance / relative entropy [61, 1]:

$$d(X, Y) = \sum_{i=1}^{k} x_i' \log_2 \frac{x_i'}{y_i'}, \text{where } x_i' = \frac{|x_i|}{\sum_{i=1}^{k} |x_i|} \text{ and } y_i' = \frac{|y_i|}{\sum_{i=1}^{k} |y_i|}. \tag{3.10}$$

Like for divergence, this metric cannot be called a distance because it is not symmetric in X and Y. A symmetrized version exists for this metric.

Correlation cofficient-based distance [53, 59]:

$$d(X, Y) = 1 - \rho(X, Y), \tag{3.11}$$

where

$$\rho(X,Y) = \frac{\sum(x_i - \mu_X)(y_i - \mu_Y)}{\sqrt{\sum(x_i - \mu_X)^2 \sum(y_i - \mu_Y)^2}}, \tag{3.12}$$

and μ_X and μ_Y represent the mean of set X and Y, respectively.

Higher order moments, based on comparing numeric representations of skewness (third moment) and kurtosis (fourth moment) [54]:

$$Skewness = \frac{E[X - \mu_X]^3}{\sigma_X^3},$$
$$Kurtosis = \frac{E[X - \mu_X]^4}{\sigma_X^4},$$

where X is a random variable, and μ_X and σ_X represent the mean and standard deviation of X, respectively.

In the higher order moments method we are looking at the degree of symmetry in the variable distribution and the relative peakedness / flatness of a distribution. The method was used by Gafurov in [24]. In this case, skewness and kurtosis of the acceleration cycles are computed and is used as a two component feature vector. This has also been done by Mantyjarvi [37], who concluded that the method was dominated by the correlation approach for his dataset.

Dynamic Time Warping (DTW) [35, 49]:

The DTW method disposes the naturally occuring changes in walking speed and is able to compare signals of different lengths, and signals where the x-axis is shifted [29]. DTW can be used for various purposes in the context of gait; it does not only have to function as a distance metric, but can also be used to calculate the average gait cycle, without having to normalize each cycle first. This ability is due to the fact that the DTW algorithm can treat sequences of different lengths. DTW has already been generally introduced in Section 3.3.4, and the implementation specific to this thesis is presented in Section 4.3.7.

3.3.7 Comparing Methods

There is no simple answer to which method is ”best”, according to [20] the results are too dependent on the environment setting, experiment design, how and where the sensors are attached and how the data is intended to be used. The state of gait biometrics also suggests that it is too early to jump to conclusions on the analysis.

Results can also vary according to pre-processing methods, method of collection, sensor sample rate and similar factors. This is also stated in [29], where Holien further discusses the quality of different methods and draws forth DTW, the histogram similarity method, correlation and the average cycle method as the most promising methods at that time.

Table 3.1 summarizes the findings of much research, and especially gives insight into results for different sensor hardware. For the (mathematical) methods discussed in this chapter, Table 3.4 provides an overview. These results are from [29], where Holien puts much effort into fine-tuning his methods. In his study, mean and median based templates used in combination with DTW, gives very good results.

For further comparison, Table 3.5 shows the performance achieved for some other biometric traits. These values are far better (lower), which illustrates the immaturity of gait technology.

	Means	**Medians**	**Trimmed means**	**DTW**
Manhattan	3.62, 3.85	3.96, 3.37	4.82, 4.42	N/A
Euclid	3.84, 3.76	3.89, 3.02	5.55, 4.25	N/A
DTW	1.77, 3.90	1.80, 3.76	2.06, 4.51	7.06, 9.40

Table 3.4: Comparison of distance metrics and averaging methods [29]. The horizontal lines show the distance metrics used, while the vertical ones show the averaging method. Each entry show the corresponding EER percentage, and two such are shown - without and with amplitude normalization, respectively. Here we can see that DTW used in combination with a mean-based template gives a very good result.

Biometric	**EER, %**	**Data set**
Iris	0.0259	200 subjects
Fingerprint	0.99-1.07	FVC2002 DB1 and DB2
Palmprint	0.19	7605 samples from 392 palms
Signature	1.4	619 samples and 94 subjects

Table 3.5: Performance overview of some other biometrics [22].

3.4 Spoofing Gait Biometrics

Despite much research in the field of gait biometrics, the technology has not been extensively tested in terms of spoofing attacks. To the author's knowledge the only available experiment results are from HiG, in essence constituting minimal-effort mimicking attempts. This section will present two experiments related to gait spoofing that gave very different results, and some critique emphasizing the need for more research.

3.4.1 Gafurov's Spoofing Attempt

The first experiment was conducted by Gafurov et al. [26, 25]. Gafurov looked mainly at what he called *passive impostor attempts*, and *active impostor attempts*. A passive impostor attempt is an authentication attempt where an individual submits his own biometric feature as if attempting to verify himself against his own legitimate template, but in fact he is compared to a non-self template. An active impostor attempt is an attempt when an individual changes his biometric sample with the aim to match another targeted person, and this sample is matched towards this targeted person's template.

The mimicking part of Gafurov's experiment was designed for, and carried out with 100 test subjects. The group was divided into pairs, where everyone attempted to imitate the other. In other words, everyone played both the role of attacker and victim. In total, two rounds of mimicking were performed. In the first round, the targeted person walked in front of the attacker, and in the second the attacker was mimicking alone. The only information the attacker had about the gait authentication was that the acceleration of normal walk was used as the standard.

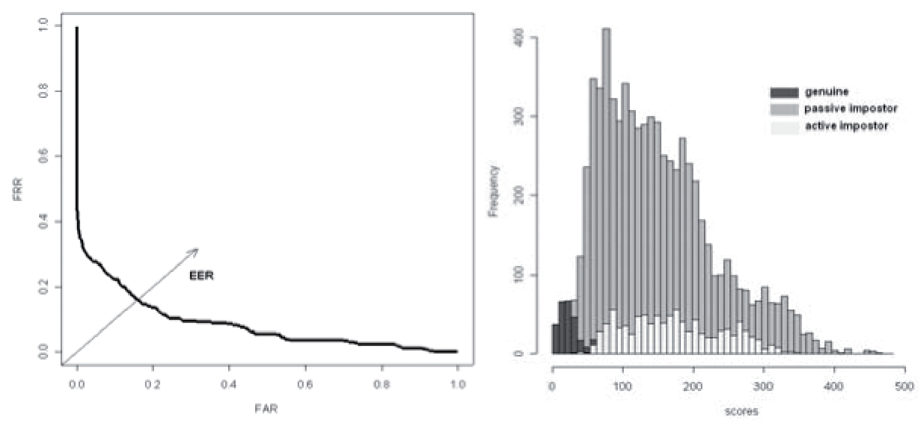


Figure 3.12: Gafurov's gait spoof experiment [26]. Left: Performance of the resultant gait signal in terms of the DET curve. Right: Distributions of genuine, passive and active impostor scores.

By also including a friendly scenario, Gafurov was able to compare the hostile scenario to genuine match scores. The left part of Figure 3.12 shows the DET curve from the friendly scenario, which characterize the performance of the biometric authentication achieved during this experiment. The achieved EER was about 16%.

For analyzing the hostile scenario, statistical techniques were applied to compare passive impostor trials and active impostor trials. The distribution of these results are given in the right part of Figure 3.12. Gafurov further tried to separate genuine and impostor trials using a D-prime value that represents the separability of two normal distributions [26]. Larger D-primes means more separability, as discussed in Section 2.5.

The results were interesting. The first observation was that the separability between genuine and active impostor trials, seemed larger than the separability between genuine and passive impostor trials. In other words, those who **tried** to mimic gait, actually did worse than those who did not. One way to explain this is that focusing on how you walk might actually make your gait unnatural and uneven. Gafurov also tested whether or not there was a significant difference in the expected mean between the active and passive impostor attempts. The results did not support such a difference. In all, this could indicate that it is hard or impossible to spoof gait by mimicking training.

However, there are several reasons why this thesis picks up the topic and continues the spoofing attempts. Gafurov performed what he called a minimal-effort study. Two attempts to mimic a person will hardly provide a valid indicator on how training or learning affects results. As we shall see in Chapter 5, the experiment designed for this thesis involves a lot more, and a very different kind of training. There will be more attempts, more sources of feedback and more time devoted to the training.

3.4.2 Stang's Spoofing Attempt

The second experiment on spoofing gait biometrics was designed and conducted by Stang [53]. A total of 13 participants contributed with 15 attempts of mimicing, in a very different setting from that of Gafurov. The trials were performed indoors, in a room where a projector displayed graph information about the victim's gait (see Figure 3.13). This was meant to be the main source of feedback for the impostors, along with a short, informal description of the gait they were targeting. This could for instance be ”normal” or ”slow” walk.

The participants watched the graphs while walking, as it was dynamically updated. Each attempt lasted five seconds, and the experiment lasted about 20-30 minutes in total. After each attempt a match score between 0 and 100 was displayed, based on correlation such that 100 is a perfect match.

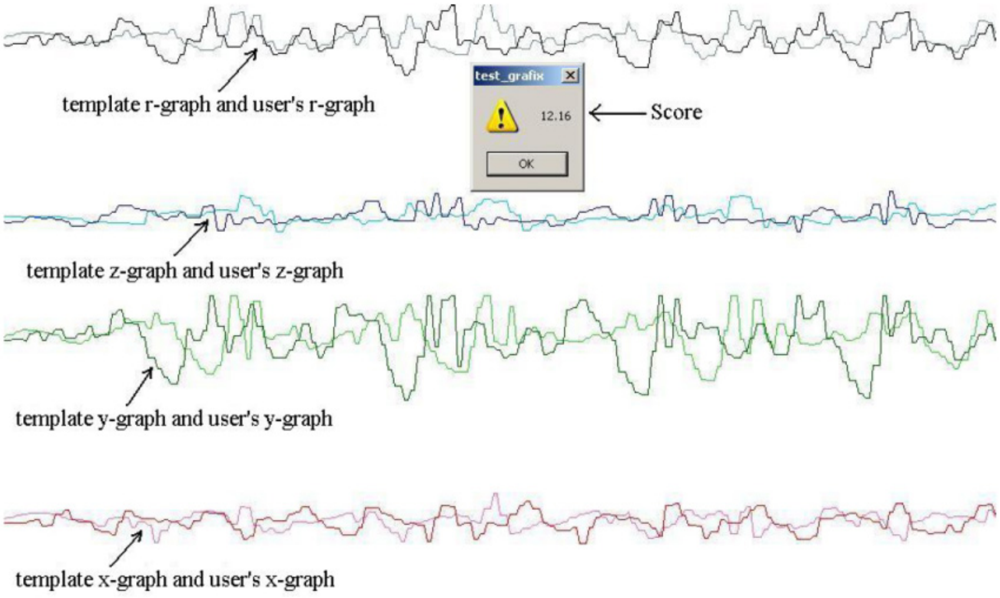


Figure 3.13: Stang's gait graphing. The graphs were displayed on the wall along with a correlation-based match score feedback to impostors.

Stang used linear regression in order to see how match scores develop from trial to trial, and used the angle of this regression to identify improvements. According to Stang, these improvements were indeed present [53], and based on this observation, along with ”high” correlation-based match scores, he concluded that learning to spoof gait biometrics seemed ”rather easy”.

It is interesting how these results disagree with those of Gafurov [26]. Some critique on Gafurov’s experiment was presented in the preceding section, and Stang’s experiment should also be criticized. Let us look closer at his methods.

As Stang describes in [53], a number of gait cycles from the victim are presented as a continuous graph, let us denote this template by A, and an attacker tries to produce a similar gait, B. The two graphs are then compared using *Pearson’s product-moment correlation cofficient*. If we let μ_X be the mean of set X, then this coefficient can be expressed as:

$$\rho(A,B) = \frac{\sum (a_i - \mu_A)(b_i - \mu_B)}{\sqrt{\sum (a_i - \mu_A)^2 \sum (b_i - \mu_B)^2}}, \tag{3.13}$$

where a_i and b_i are the i-th values of A and B, respectively. This is a well known correlation cofficient from statistics [6]. Correlation tells us how strong the linear connection is between the two sets A and B. The result ranges from -1 to 1, where the higher absolute value indicates that the sets are strongly connected, as discussed in Section 2.5.

Stang further attempts to establish an interpretation of what is considered high and low correlation. He does this based on a **psychological** study by Jacob Cohen [15]. This study suggests that the following ranges and interpretations apply:

$|\rho| \in [0.10, 0.29]$ perceived as small or low,
$|\rho| \in [0.30, 0.50]$ perceived as medium,
$|\rho| \in [0.50, 1.00]$ perceived as large or high.

After collecting impostor data, Stang analyses the findings relative to three different acceptance thresholds. He does not state how he selects these three threshold values, 40, 50 and 60, they look rather ”random”. However, since he includes the psychological interpretations of ρ it is reasonable to believe that he had these intervals in mind - selecting one medium value, one high value and one value in between. One obvious disadvantage is the projection of psychological perception onto security strength. A requirement of 60% match in a biometric sample is not very strict, and we cannot base security on human perception in general. The values could have been based on a ”friendly” scenario, where users are enrolled in order to find thresholds corresponding to the EER, but this is not the case in Stang’s work. The thresholds selected are very low, and according to some test subjects it was rather easy to beat these thresholds by simply syncronising the footstep timing.

Another drawback in Stang’s work is the way he attempts to identify learning. His approach consists of doing a linear approximation where he looks at the angle of the fitted curve, and draws conclusions based on his own impression of its steepness. The report does not present any valid statistical tests made on the data, and no confidence intervals or measures of fit are provided. This is a very unfortunate way of constructing a learning curve - the linear model does not converge, and thus goes to positive or negative infinity over time, which has no meaning in the context of learning. Without hypothesis testing his conclusions are not justifiable, and the curve itself is based on very few data points, making the approximations extremely uncertain. The data points are few in the sense that the number of impostor attempts were low, but also that the ZSTAR gait collector used in this research sampled only 30 times per second, as opposed to the MR100's 100.

There are more factors that increase the level of uncertainty in Stang's work. The correlation is calculated from the whole gait sequence, and two such sequences have to be synchronized in order to even get a chance to match. In fact, a "perfect" verification sample could easily be rejected if it was out of sync - say if the footsteps were shifted in time by half a gait cycle. Stang does not perform any kind of graph shifting or synchronization. The case is the same for gait cycles - since the sequence is treated as a whole, gait cycles are completely ignored. In comparison Gafurov uses a self-developed method to identify and average gait cycles [21, 24, 26]. Paying attention to the characteristics of the gait cycles have paid off in previous research, and it reduces undesired effects (e.g. from irregular cycles). This alone does not mean Stang's match score becomes too high, but increases the general uncertainty of his results.

Finally, Stang's experimental environment is unfortunate. The mimicking is based on a five second walk, which is rather short when considering the high probability of an unnatural start and finish. Walking towards a wall with a projected image on it, trying to adjust the gait according to a graph, is also an unnatural setting that could bias the performance.

3.5 Contribution

The critique presented in the previous section section should be sufficient to convince the reader that the research on gait security must continue. In this thesis the author will concentrate on gait mimicking and hopes to advance knowledge in the field by taking test subject training to a higher level.

With personal coaching for several sessions, and with more selective use of feedback sources, the author hopes to create a better ground for mimicking attempts. The main goal is to identify a learning curve for the test subjects, to determine how the training affects their results over time, and to learn how far this training can advance their skills.

Since this is a Master's and not a PhD Thesis, time is too short for an experiment involving a large number of test subjects. However, the results will hopefully constitute a set of valuable indicators, and the author hopes that researchers and students choose to extend his work by improving experiment design and increasing its volume in terms of participants.

Chapter 4

Choice of Technology

With the state of the art presented, the reader should now have a certain overview of research, results and methods related to gait biometrics. This chapter will present the choice of hardware equipment (the gait collector), and the methods used in the developed application prototype.

4.1 The Choice of Gait Collection Hardware

For the gait collection HiG provided two wearable sensors: the Motion Recording 100 (MR100)[1], and the Freescale ZSTAR sensor. The latter sensor is a commercial product with a 2.4GHz Wi-Fi interface, and can be seen in Figure 4.1 together with the MR100. The MR100 does not have the advantage of a wireless interface, it uses a mini-USB, but it still has a great advantage over its wireless competitor - the sample rate. The MR100 takes approximately 100 samples per second, while the Freescale takes about 30 [53, 10].

The MR device is the only device actually used in this thesis, mainly due to its higher sample rate. This will allow for more reliable measurements, and more accurate gait analysis [10]. The MR sensor measures acceleration in three orthogonal directions, up-down, forward-backward and left-right. In other words we may say that the measuring sensors of the device exhibits six degrees of freedom. The sensor also includes an internal memory of 64MB for storing acceleration values, and a rechargeable battery [22].

4.2 The Choice of Hip Attachment

There are numerous possibilities regarding sensor attachment, research by Gafurov, Ailisto and others utilized several different body parts such as hip (belt or pocket), lower leg and arm [4, 3, 11, 21, 24, 22], discussed in Chapter 3.

Previously this thesis provided a hint on the choice in this matter: a cell phone that can identify its user based on his or her gait. Several portable devices such as cell

[1] The MR100 has been developed at HiG.

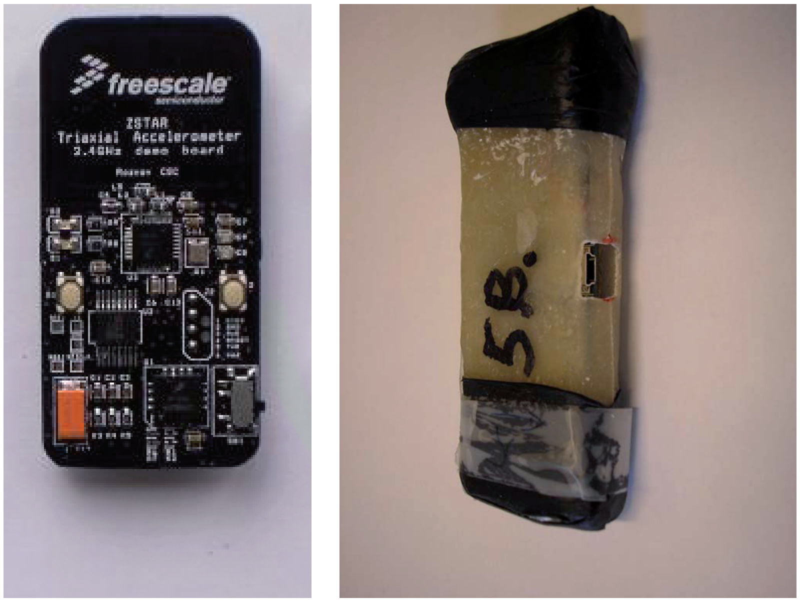


Figure 4.1: Available gait collection hardware. Left: The Freescale ZSTAR wireless accelerometer [53]. Right: The MR100 accelerometer [22].

phones and PDAs are in need of secure authentication mechanisms, and these are typically carried in the hip area. The fact that devices like these are so extensively used in the modern world, makes this a good reason to use hip attachment.

When analyzing hip movement, we can again choose from a few different attachment points. One is the pocket, but this location has some disadvantages. The main disadvantage here is that it is difficult to know the exact orientation of the device. It is also difficult to attach it in a stable manner inside pockets. Other challenges present themselves due to the design of the clothing; pockets vary in size, shape and location, and some jeans may not have pockets at all.

For these reasons the belt has been chosen for attachment (see Figure 4.2). The belt can be mounted to any person's hip regardless of what they are wearing. The device will always have the same orientation, and it will be visible at all times. EER values achieved for hip based gait authentication in general range from 2% to 13% [22], so the hip is a good choice also due to maturity.

4.3 Methods for Gait Analysis

There is little software available specifically developed for gait analysis. The thesis used a HiG-developed application for transferring the raw data from the MR100 to the computer, and used Matlab to develop an analyzer tool. The implementation specifics of the prototype tool will be described here, while Matlab code can be found in Appendix B.

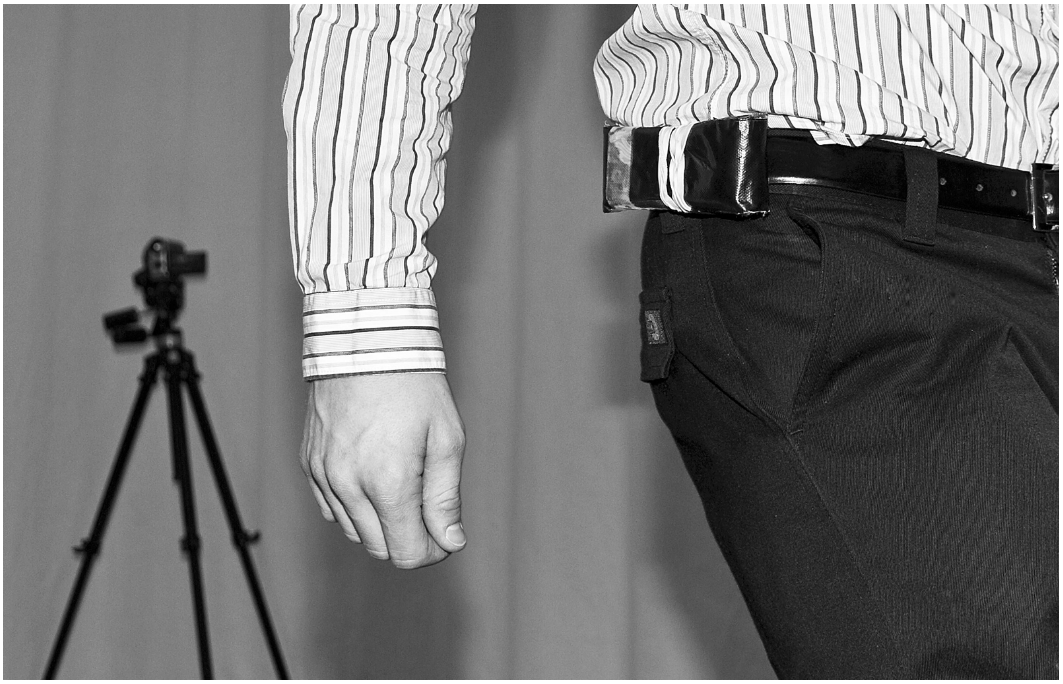


Figure 4.2: Gait collector attached to the hip, a video camera on a tripod in the back.

The thesis' approach to gait analysis is a configuration of existing methods seen in Chapter 3. The principle of cycle detection and averaging is applied, and optimizations are based on experimenting and previous research.

In short, the raw data will be preprocessed by interpolation and filtering. A translation into G-forces is also convenient. After this, we compute the resultant acceleration for the gait data, and estimate the length of the cycles. This estimate is then used to detect the actual cycles, and normalize them. Irregular cycles are omitted through a cycle cleaning step, followed by the template creation. The template essentially consists of an average cycle of the enrolled user.

An overview of the processing is provided by Figure 4.3, and every step in this overview will be explained in detail in the proceeding sections.

4.3.1 Signal Preprocessing

Before we can look directly on the gait cycles, we need to preprocess the raw data. The acceleration values are prone to many noise factors, and the time scale might be uneven. Also, an interpretation of the device-specific acceleration values is necessary before we can work with g-forces.

Interpolation

Through experimenting it was discovered that the sample rate of the MR100 was not exactly constant. To ease further analysis of the gait signal, it is desirable to have a constant time axis with one sample every $\frac{1}{100}$ second. The raw data showed

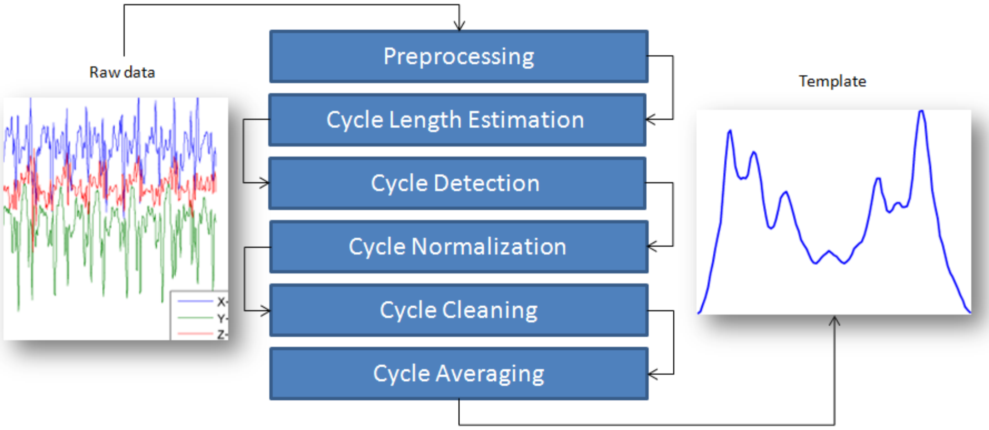


Figure 4.3: Gait Analysis Overview. The raw data will undergo six steps before a template is created. First, it is preprocessed by filtering and interpolation. Then the cycle length is estimated and used in order to detect and then normalize the actual cycles. Then the cycles are cleaned, which means omitting irregular cycles from the rest of the processing. Finally, the average cycle is calculated, which essentially constitutes the template of an enrolled user.

that the time values obtained were typically very close to the desired values, so a simple interpolation operation is adequate.

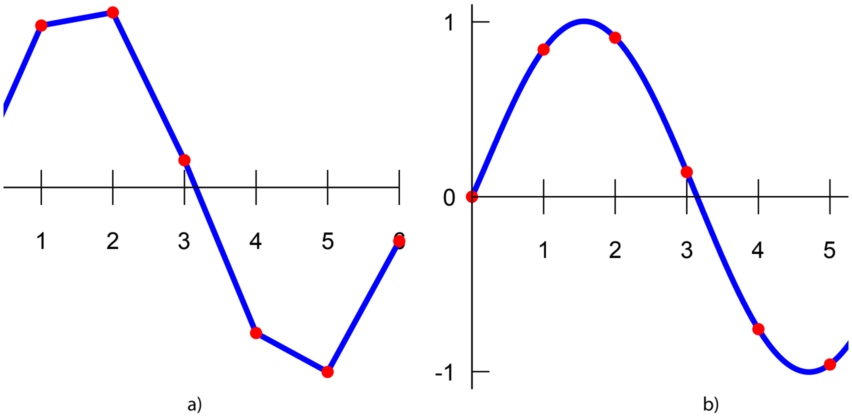


Figure 4.4: Interpolation: The figures show data plots with a) linear and b) general polynomial interpolation superimposed.

Figure 4.4 shows the linear interpolation method, and its generalization: polynomial interpolation. The latter method represents interpolation with a higher polynomial degree, but in the case of the experiment the linear version is acceptable because the time values are very close to each other. Code if found in Appendix B.1.

Filtering

The acceleration data is not ideal, it contains extreme and unwanted values due to many potential noise factors. This is a problem for biometrics in general, and the main reason why a *perfect* template does not exist for most biometrics [38]. There are many ways of removing noise from signal, and it is beyond the scope to consider them all. However, Holien considered two possible filters in [29], namely the Moving Average and the Weighted Moving Average. These concepts are illustrated in Figure 4.5 a and b, respectively.

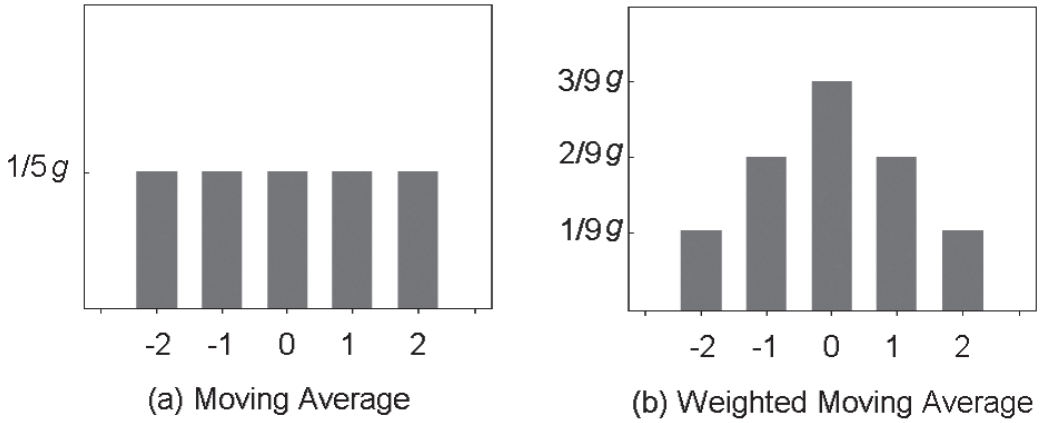


Figure 4.5: Moving average filters with and without weights [29].

The (Weighted) Moving Average filters 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 filter's 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.

As in [29], the Weighted Moving Average with window size of five is chosen for preprocessing. This is reasonable because the local peaks in the gait signal are important for cycle detection, the WMA filter will obviously preserve these characteristics better than MA filters. Code if found in Appendix B.1.

G-Force Conversion

The MR100 sensor only provides raw acceleration data, so it is necessary to perform a conversion. The values provided are all in the range $[0, 1023]$, which corresponds to the range $[-6g, 6g]$ where g is the gravitational constant of earth [10]. In an ideal world we could easily perform this conversion with the following equation:

$$y = \frac{(x - 512) \cdot 6}{512}, \tag{4.1}$$

where x is the raw sensor value, and y the new g-force value. Unfortunately, the world is not ideal and neither are the sensors, so numbers might change over time, and in general become unstable.

To solve this the device could be calibrated, but that is a rather time-consuming and expensive task. Holien experimented with the device in [29] and this thesis first tried to adopt his adjustment scheme. It basically consist of finding constants that shift the range of g-forces back to the intended normal. However, in the end new constants had to be found, due to further deviations since Holien's work. Code if found in Appendix B.1.

Resultant Calculation

At this point we are dealing with acceleration in three dimensions, and we need to construct a combination of these in order to create a template for the user. Many combinations have been tried, some of them are very simple, even excluding specific dimensions [3], while others are more sophisticated [19]. In this thesis we will use the resultant of all dimensions:

$$r_t = \sqrt{x_t^2 + y_t^2 + z_t^2},\ t = 1, \ldots, n \tag{4.2}$$

where r_t, x_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 samples.

4.3.2 Cycle Length Estimation

In order to ease the process of detecting cycles, we want to obtain an estimate of how long each cycle is. Normal walk constitutes about 100 samples from the MR100 [10], but this is not accurate enough. People will differ according to the length of their legs, their weight and walking speed. So prior to any cycle detection, we want to perform an automatic estimation of the cycle length.

In this thesis a correlation-based approach from [29] is used. A subgraph from the middle of the gait sequence is extracted and compared to other parts of the graph (see Figure 4.6). By calculating the correlation between the subgraph and other parts of the graph, and remembering the positions with the best match, we can simply average over the distance between each of these positions. If the starting point of the subgraph is in the middle, then we will typically get high correlations 100 samples before or after the middle, and the same for 200 samples and so on.

Some fine-tunings of this method have also been made. Problems can arise from irregular cycles, such that we might miss a point where the correlation is supposed to be high. In other words, we might miss a step in our estimation - this will give the impression that some steps are very long compared to others. Typically these outliers will have a length that constitutes some multiple of the actual cycle length. Here lies also the key on how to solve problem, the "hidden steps" are found by splitting the cycle lengths into shorter instances, and comparing it to the expected length. For instance, a cycle length of 220 is definitely too long to count as one cycle, but half of it, 110, can be used instead.

Table 4.1 shows the pseudocode of the process. MATLAB code if found in Appendix B.2.

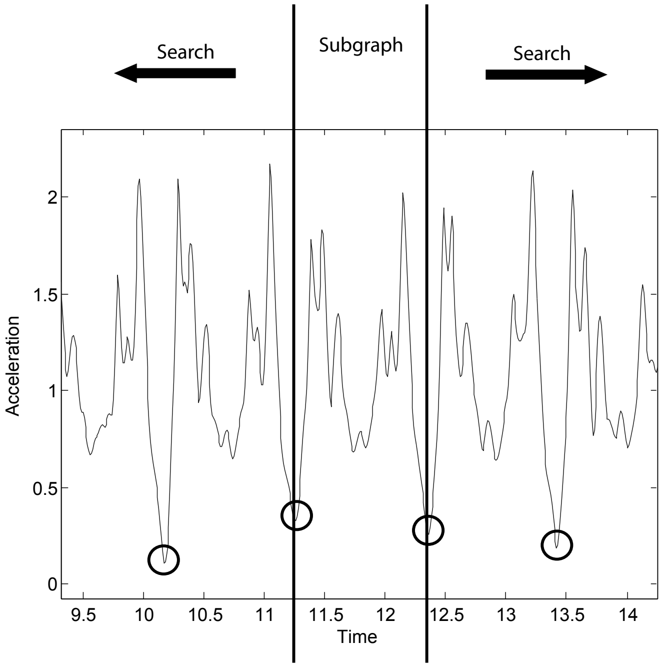


Figure 4.6: Cycle length and cycle detection. A subgraph is extracted from the main signal (subgraph) and compared to other parts of the graph. The highest correlations indicate matching positions, and the distance between two samples in two subgraphs constitutes a cycle. The circles represent possible starting locations of the subgraph, and averaging over the distance between these yields the estimate.

```
ESTIMATE CYCLE LENGTH($gaitsignal, width, threshold$)
$subgraph \leftarrow$ extract $width$ samples from the middle of $gaitsignal$
$highcorrelations \leftarrow$ vector of zeroes
for the whole search area
    do
        $comparison \leftarrow$ extract $width$ samples from search area in $gaitsignal$
        $correlation \leftarrow correlation[subgraph, comparison]$
        if $correlation > threshold$
            then $highcorrelations \leftarrow$ add $correlation$
return $cyclelength \leftarrow$ average distance between peaks in $highcorrelations.$
```

Table 4.1: Cycle length estimation pseudocode. Matlab code provided in Appendix B.2.

4.3.3 Cycle Detection

The ”actual” cycle of a person could be defined to start when the right foot is lifted, and end when that foot is back in the same position. This cycle is represented by Figure 4.7. However, when dealing with the data we are free to define the cycle as we want, and the easiest way would be to look at characteristics in common of the gait cycles, regardless of person.

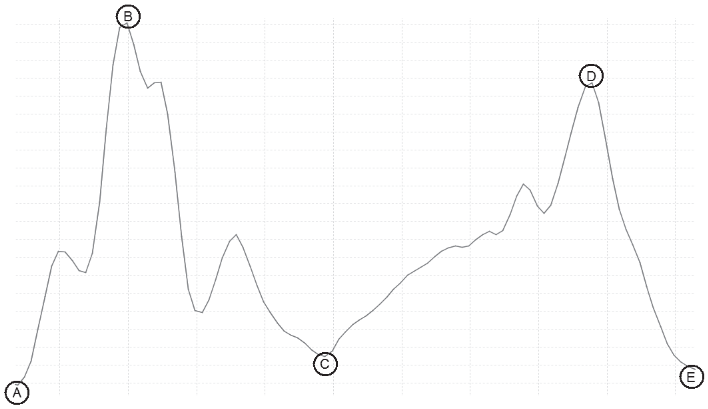


Figure 4.7: An actual "correct" gait cycle [29]. A = start of the step, B = first maximum, C = local minimum, D = last maximum and E = end of the step.

Looking at the gait example in Figure 4.8, the reader might observe many characteristics of the repetitive pattern, such as the "M-shape" of gait cycles. Hence, in this thesis we will not concentrate on what is referred to as the "actual" cycle, but rather any cycle defined between two repetitive characteristics. As the figure shows, the local extrema are clearly visible. In this thesis, the minima are used for gait cycle detection. The process will be described here, followed by pseudocode. Let N be the estimated cycle length (see Section 4.3.2) and L the length of the entire gait sequence.

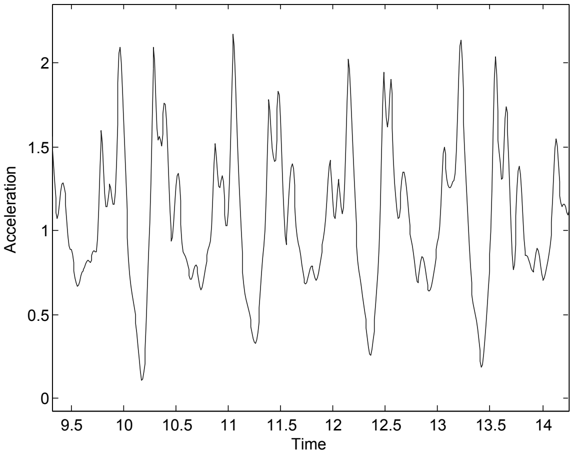


Figure 4.8: A gait sequence example. Notice extrema that repeats throughout the signal, and the "M-shaped" cycles.

1. The minimum 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. Hence, $M \in [0.5L - 1.2N, 0.5L + 1.2N]$.

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

3. A search is made backward in the gait signal by jumping N steps in this direction, and scanning the new point for another minimum, with a buffer of 10 samples 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 for the rest of the thesis. Hence, we now know the exact location of each cycle.

Matlab code provided in Appendix B.2, while the pseudocode is shown in Table 4.2.

```
CYCLE DETECTION($gaitsignal, cyclelength$)
$startingpoint$ ← minimum in the middle area of $gaitsignal$
    do
        $cycles$ ← minimum of $gaitdata$, $[k \cdot cyclelength \pm 10]$
        samples away from $startingpoint$ for all integers $k$ in range
    until all $gaitdata$ has been searched
return $cycles$
```

Table 4.2: Cycle detection pseudocode. Matlab code provided in Appendix B.2.

4.3.4 Cycle Normalization

In order to perform the averaging of gait cycles, we need all the cycles to be of the same length. Several noise factors can cause the number of samples to fall short or exceed the average. Hence, the deviating cycles has to be stretched or shrunk in order to fit the desired range of samples. There are three possible scenarios for this problem.

The first situation is when a cycle exhibits the exact desired length. That is, it is equal to the overall cycle length average. In this case, we can keep the cycle exactly as it is, no further processing is necessary.

The second scenario occurs when a cycle is shorter than the average, this can be solved by interpolation. The easiest way to think of this process is that we first stretch the signal to the desired length, or equivalently shrink the timeline until the signal has the desired length. Now the challenge is purely about missing and shifted samples, and these can be found by interpolating in the same way as described in Section 4.3.1.

The third scenario is when a cycle is longer than the average. In this case we do the exact opposite of the second scenario, we shrink the signal (or equivalently, stretch the timeline) such that the correct time span again is covered by the gait sequence. Now we have too many samples, most probably also out of sync with the sample rate, so we interpolate to obtain the correct values. Figure 4.9 shows a gait sample, and its detected cycles before and after normalization. The following steps are performed:

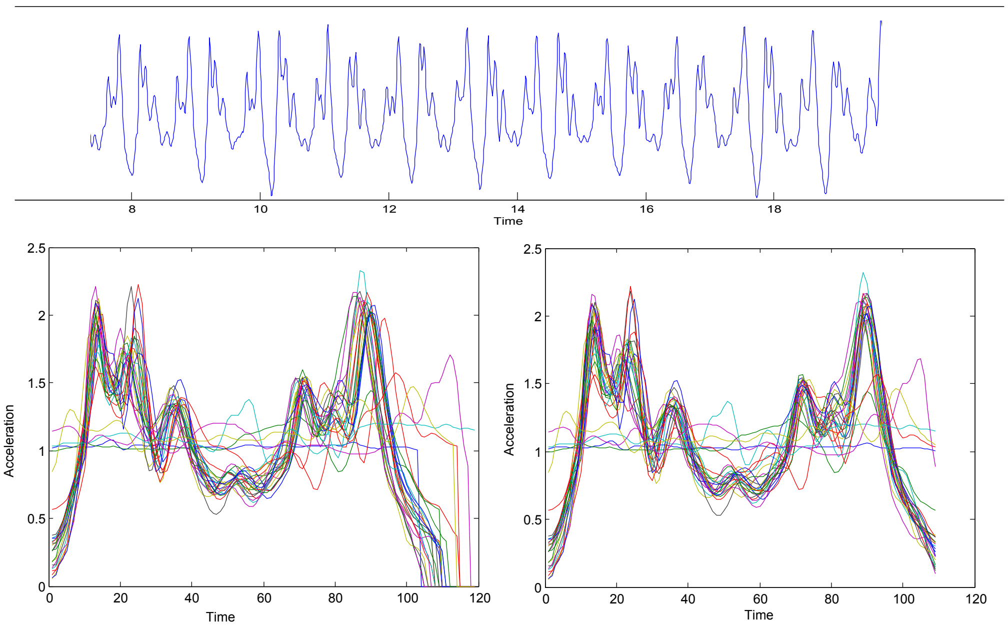


Figure 4.9: Gait cycle normalization. The figure shows a gait sequence (top), its detected cycles plotted on top of each other (bottom left) and the cycles after normalization (bottom right).

1. Based on previously obtained data, extract the full cycles and store them in a set $\mathcal{S}$.

2. Let L_{avg} be the average cycle length, and L_s the length of a sequence s. For all $s \in \mathcal{S}(L_s \neq L_{avg})$, construct a new timeline for s, T_s, in the following way: starting at $\frac{1}{100}$, produce all numbers from this point until $\frac{L_{avg}}{100}$ is reached, using steps of size $\frac{L_{avg}}{L_s}$, where L_s is the length of cycle s.

3. Perform linear interpolation based upon the original resultant values of s, the new timeline T_s and the desired timeline T_x. T_x consists of every step of size $\frac{1}{100}$, from the starting point $\frac{1}{100}$ to the ending point L_{avg}.

Table 4.3 shows the pseudocode of the process.

4.3.5 Omitting Irregular Cycles

To optimize the results we want to exclude outliers before we calculate the average cycle. This can be done in many ways, DTW will be used in this thesis (see Section 4.3.7 for DTW details).

The process is simple, every (normalized) cycle is compared to each other in terms of DTW distance, and each cycle's average DTW relative to every other cycle is calculated. Then, the grand DTW average is computed taking the mean of these

```
CYCLE NORMALIZATION($cycles, resultant$)
$averagelength$ ← average length between indexes in $cycles$
for all starting indexes $i$ in $cycles$
    do
        $cycle$ ← extract $averagelength$ samples starting from $resultant[i]$
        $fullcycles$ ← add $cycle$
for all cycles $c$ in $fullcycles$
    do
        $c$ ← adjust cycle length to $averagelength$ by interpolation
        $normalizedcycles$ ← add $c$
return normalizedcycles
```

Table 4.3: Cycle normalization pseudocode. Matlab code provided in Appendix B.2.

values. Finally, every cycle's average is compared to the grand average - if the value is too far from the grand average the whole cycle is omitted from the cycle set. The process is repeated for a series of ”sliding” thresholds, decrementing in size.

More formally, the steps are as follows:

1. Generate an all-to-all DTW matrix $\mathcal{M}$, comparing every cycle to every other: $\mathcal{M}(i, j) = DTW(cycles(i), cycles(j))$.

2. For all cycles i, compute the average DTW from i and all other cycles: $dtwavg(i) = \sum_j \mathcal{M}(i, j)/n$ where n is the total number of cycles.

3. Compute the grand DTW average, meaning the average distance from a cycle to all other cycles: $grandavg = \sum_i dtwavg(i)/n$, where n is the total number of cycles.

4. For a threshold t, delete all cycles i with DTW average ($dtwavg(i)$) deviating from the grand average with more than $t \cdot 100\%$.

5. Repeat this process for all pre-defined thresholds. Trial and error resulted in the following choice of thresholds for this thesis: $\{0.7, 0.5, 0.3, 0.2\}$.

Matlab code provided in Appendix B.2.

Figure 4.10 shows how remarkably well this process can ”clean” a set of gait cycles. Many irregular cycles are usually discovered, and none of these will affect the final results.

4.3.6 Cycle Averaging

With all cycles normalized to the same length, calculating the cycle average is technically straightforward. However, the choice of averaging tool is a different story because performance is prone to degradation from outliers. To solve this, proper preprocessing and a wise choice of averaging tool is necessary.

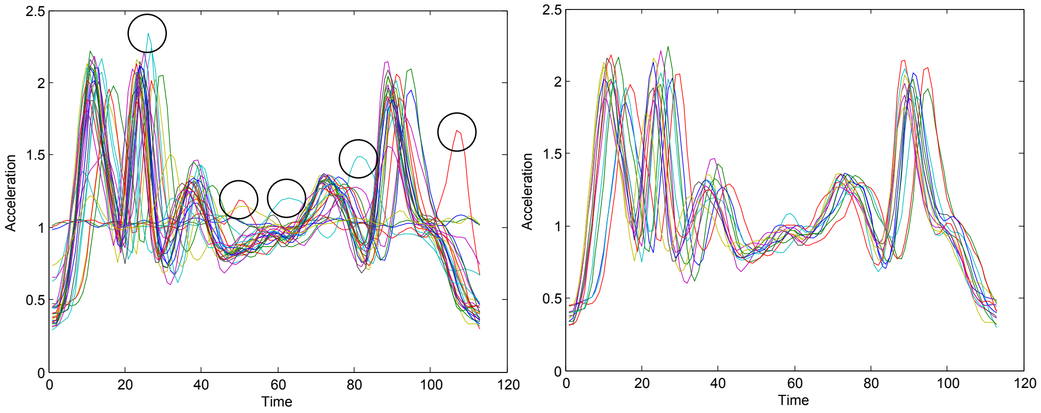


Figure 4.10: Omitting irregular gait cycles. The left graph shows the original cycles, and the right graph shows the set of cycles after removing outliers. The circles provide examples of extrema and irregularities that will not affect the final results.

In this thesis, we have already removed irregularities from the set of cycles (see Section 4.3.5). Hence, the mean will be used and we need not worry about outliers. Using the mean together with removal of irregular cycles, result in what we can call a ”trimmed” mean.

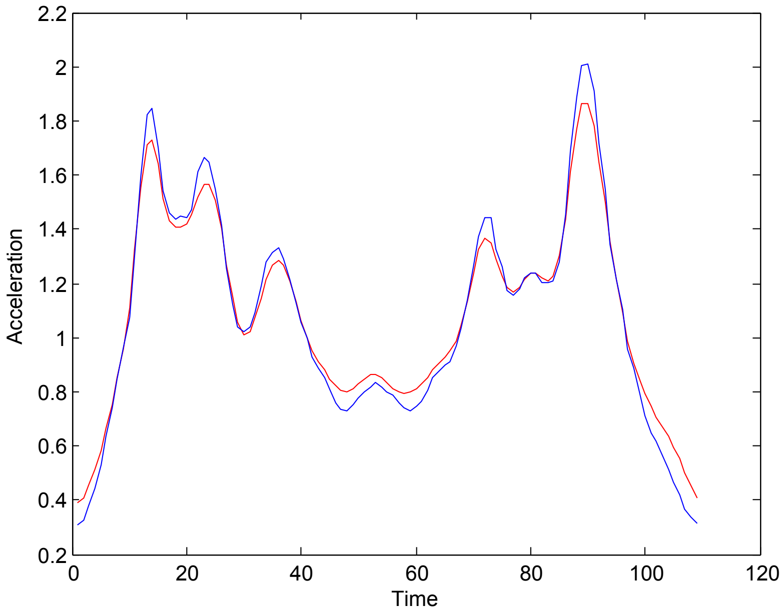


Figure 4.11: An averaged gait cycle, showing the mean averaging in red and median averaging in blue.

The average cycle is computed as described in Section 3.3.1, Gafurov’s cycle length method. We let each sample in the cycle belong to a group or set, and average these values. In other words, in a matrix filled with cycles where each row constitutes a new cycle, each column would represent one group. The mean is found simply by averaging over the columns.

Figure 4.11 shows the result from both mean- and median-based averaging. Matlab code provided in Appendix B.2.

4.3.7 DTW-Based Gait Comparison

The outcome of all the previous processing is an average cycle, which is used as a template. Now the time has come to look at the authentication - where we essentially want to compare one template to another. Dynamic Time Warping (DTW) was presented in Section 3.3.4. For this thesis, a modified version of DTW will be used, based on [29, 13] and new trials.

Cost Calculations

Consider a sequence of numbers $\mathcal{T}$ of length n, which constitutes an enrolled gait cycle average, a template. Also, let $\mathcal{Q}$ be the gait cycle average in question, of length m - submitted in order to be verified against the template. We define

$$\mathcal{T} = \{t_1, t_2, \ldots, t_n\} \tag{4.3}$$

$$\mathcal{Q} = \{q_1, q_2, \ldots, q_m\}, \tag{4.4}$$

where $t_i \in \mathcal{T}$ and $q_i \in \mathcal{Q}$ are acceleration values with index i.

Similarily to what described in Section 3.3.4 we construct a matrix and let cell (i, j) represent the cost of transforming the subsequence of length i, to the subsequence of length j. The following costs are used:

- **Insertion cost:** $\mathcal{C}_{ins}(x) = 0.5$, where x is the inserted value.
- **Deletion cost:** $\mathcal{C}_{del}(x) = 0.5$, where x is the deleted value.
- **Substitution cost:** $\mathcal{C}_{sub} = \frac{|x-y|}{S}$, where x and y are the values going out and in, respectively, and $S = \max(t_1, \ldots, t_n, q_1, \ldots, q_m) - \min(t_1, \ldots, t_n, q_1, \ldots, q_m)$.

These values are obtained from [29], where Holien justified the choice of the two first costs by his own experiments. Trial and error gave good results for these constants. The substitution cost is quite intuitive, the absolute distance between the two values are divided by S, which is the maximum distance among all numbers in the template and the sequence in question. Hence, the substitution cost will be in the range $[0, 1]$.

The cost matrix $\mathcal{M}$ is constructed in the following way [29]:

$$\begin{aligned}
\mathcal{M}(1,1) &= 0.00, \\
\mathcal{M}(i,1) &= \mathcal{M}(i-1,1) + \mathcal{C}_{del}, \\
\mathcal{M}(1,j) &= \mathcal{M}(1,j-1) + \mathcal{C}_{sub},
\end{aligned}$$

for $i = 2, \ldots, n+1$ and $j = 2, \ldots, m+1$. This merely reflects the boundary condition and the costs of pure deletions and insertions, respectively. Further:

$$\begin{aligned}\mathcal{M}(i,j) = \min\{ & \\ & \mathcal{M}(i-1,j-1) + \mathcal{C}_{sub}(t_i, q_j), \\ & \mathcal{M}(i-1,j) + \mathcal{C}_{del}, \\ & \mathcal{M}(i,j-1) + \mathcal{C}_{ins}\},\end{aligned}$$

for $i = 2, \ldots, n+1$ and $j = 2, \ldots, m+1$. This fills out the rest of the matrix, looking at cell (i,j) and selecting the cheapest path from its three completed neighbor values to itself.

		0.5	**0.4**	**0.9**	**1.7**	**2.2**	**1.9**	**1.1**	**0.1**
	0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0
0.1	0.5	0.16	0.62	1.12	1.62	2.12	2.62	3.12	3.5
0.2	1.0	0.62	0.24	0.74	1.24	1.74	2.24	2.74	3.16
0.4	1.5	1.04	0.62	0.44	0.94	1.44	1.94	2.44	2,86
0.8	2.0	1.54	1.12	0.66	0.8	**X**			
0.4	2.5								
1.5	3.0								
2.6	3.5								
2.5	4.0								
1.1	4.5								
0.3	5.0								DTW

Table 4.4: DTW example on gait comparison. The first row and column represent number sequences, which in this case are gait acceleration values. When the table is complete, the bottom right cell contains the DTW metric. Other implementations may mirror this method, and work in the direction of a different corner.

Obtaining the DTW Metric

Table 4.4 provides an example of an incomplete cost matrix, the first row and column represent number sequences, which could be gait acceleration values. The X is calculated according to the DTW algorithm:

$$\begin{aligned}X &= \min\{0.8 + \mathcal{C}_{ins}, 1.44 + \mathcal{C}_{del}, 0.94 + \mathcal{C}_{sub}(0.8, 2.2)\} \\ &= \min\{0.8 + 0.5, 1.44 + 0.5, 0.94 + \frac{|0.8 - 2.2|}{2.6 - 0.1}\} \\ &= \min\{1.3, 1.94, 1.5\} = 1.3\end{aligned}$$

The matrix is used to compare gait cycles, and the bottom-right cell will contain the DTW distance metric. When several templates are available, we do this calculation for every pair. This is needed to create a DET curve.

MATLAB code for DTW is provided in Appendix B.4.

Enhancing Comparison with Time Shifting

When a template (i.e. an average gait cycle) is compared to a candidate gait sample, steps can be out of sync. That is, even if the candidate constitutes a genuine verification attempt, a poor score may be produced because the average cycle is shifted in time. This can be difficult to predict, especially since numerous interpretations of the same cycles are equally stable and valid. If we do not cope with this problem, the FNMR will be high.

In this thesis, gait cycles will be compared to each other directly, but they will also be circularly shifted to check if the DTW distance decrease as a consequence of this. The most accurate, but also most time consuming configuration for this method is to shift one cycle one sample at a time, calculating the DTW for each position, and use the lowest score. In this thesis however, we will ease this task in favor of speed.

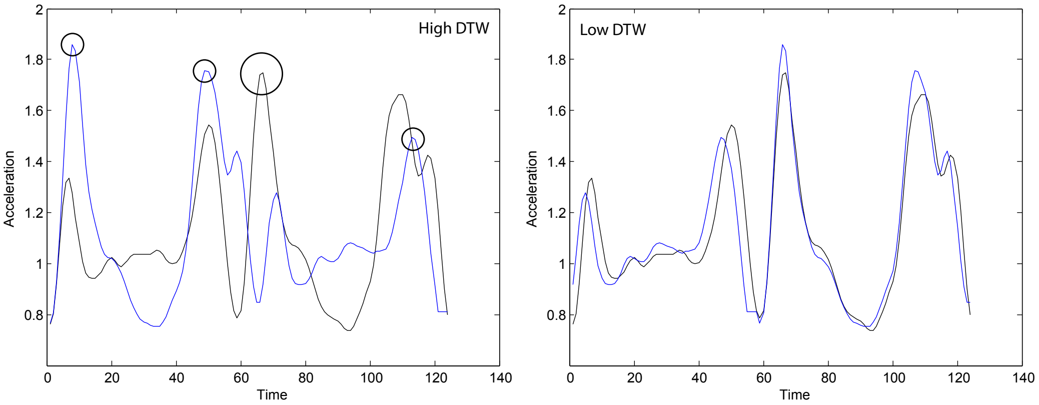


Figure 4.12: Time shifting of out-of-sync cycles. Left: Two average cycles from the same person are out of sync and will produce a high DTW score. The template maximum is represented by the large circle, and three identified maxima in the candidate cycle are marked with small circles. Right: The correct shifting has been found, aligning the candidate relative to the template maximum produces a much lower DTW.

The method works as follows: the largest value in the template is identified, as well as four maxima above a certain threshold in the candidate cycle. The candidate is shifted as many times as the number of maximas found, and the DTW is calculated for each of these. Among these, and the original non-shifted DTW, the lowest value is used. Figure 4.12 illustrate the process.

More formally, the steps are as follows:

1. Calculate the DTW distance between the cycles i and j: $distance = DTW(cycle(i), cycle(j))$.

2. Find the maximum acceleration peaks in i and j, filter out those lower than a chosen threshold and store up to four of the remaining peaks for each cycle.

3. For the cycle i with the highest number of stored peaks: find the absolute maximum M.

4. Circularly shift cycle j such that the first stored peak in j is aligned with M. Compute the DTW for this configuration, and compare the result with $distance$. Replace $distance$ with the smallest number, and repeat the process for all peaks stored for j.

4.4 Chapter Summary

This chapter has presented the thesis' choices in both hardware technology, and analysis methods. The MR100 gait collection device has been chosen mainly due to its high sample rate, and the hip has been chosen for attachment point. As many mobile devices are carried in the user's pocket, hip-based gait biometrics constitutes a realistic scenario.

The software tool developed for the experiments is implemented in MATLAB, and the most important features are:

- Signal preprocessing is performed using interpolation and WMA.
- The cycle length is estimated using a correlation-based method.
- The cycles are identified using their local minima as starting points.
- The cycles are normalized to a fixed length by interpolation.
- An average cycle is generated from the normalized cycles using trimmed mean.
- DTW with time shifting is used as distance metric when comparing cycles.

Pseudocode was included in this chapter where it was considered valuable, and the exact MATLAB code is included in Appendix B.

Chapter 5

Experiment Design

In Section 1.3 the author presented the scope and objectives of the thesis. It included research questions that can only be answered through an experiment. This chapter will present the design of the experiment and details on how it was conducted.

5.1 Experiment Description

The experiment can be divided into three scenarios:

The friendly scenario consisted of collecting regular gait data from a test group. The subjects did not receive much instructions or training, but simply walked a fixed distance while wearing a sensor. This allowed the calculation of error rates and provided a basis for comparison with other parts of the experiment.

The short-term hostile scenario was based on some of the subjects from the friendly scenario. The author created a group of attackers who attempted to imitate one specific victim. The group was quite small, and consisted both of people who were already walking somewhat similar to the victim, and of people who walked differently. The choice of a small group size is justified by the amount of effort and time put into the training, there was not enough time to conduct this experiment with a high number of attackers.
After each imitation attempt, the attacker was able to review his or her own gait on a video recording, and further improve the mimicking by comparing it to a video of the victim. Statistical results was also available. One session took about an hour, and five sessions were held for each attacker.
This scenario constitutes the main part of the experiment, and provides insight on whether or not mimicking skills can be elevated to a sufficiently high level to spoof gait biometrics.

The long-term hostile scenario had only one test subject. The attacker trained to mimic the victim in the same way as the other attackers did, but in this case there were more sessions, over a longer period of time. This was particularly interesting because during the short-term scenario, the author gained insight in every previous attempt to mimic the victim. Hence, this scenario had a much better foundation of experience. The long-term hostile scenario was planned to endure for as long as possible, towards the submission of the thesis.

5.2 Terminology

In order to be able to describe the details of the experiment in a specific, non-ambiguous way, some terminology must be defined.

A CYCLE consists of two gait strides, or steps, ending when both feet are back in the starting position. There is no rule to where a CYCLE should start and end, a convenient point is found by the algorithm. More on this in Section 4.3.3.

A WALK is a set of consecutive CYCLES. If a person stands still, walks a distance, and then stops, the cycles in between of the still positions constitute a WALK.

A GO consists of all gait information from the point where the sensor is activated, and until it is turned off. One GO consists of one or more WALKS, and different GOs can be composed in unequal ways (i.e. GOs for different scenarios and participants can contain varying number of WALKS and CYCLES).

5.3 Environment and Volunteers

The experimenting process was mostly conducted at Gjøvik University College (HiG). That is, the friendly scenario and the short-term hostile scenario were both carried out at this location, while the long-term hostile scenario was carried out in two locations: HiG and NTNU.

All experiments were conducted indoors, to eliminate some noise factors (i.e. climate conditions). The same floor material was used in every setting.

For the friendly scenario, 50 test subjects from HiG were used, consisting of 14 females and 36 males. The test subjects were all between 19 and 66 years old, and the total mean and median were 23 and 26.8 years, respectively. Figure 5.1 shows the complete gender and age distribution of the participants. All subjects agreed to a participant agreement declaration, and provided basic information about themselves such as height and weight. The declaration and the participant registration form can be found in Appendix C, but as stated all the data has been destroyed. All volunteers for this scenario either reported in after an e-mail request, or they were offered to participate at random locations within the college.

Seven of the participants from the friendly scenario were asked to attend the second part of the experiment, the short-term hostile scenario. They all accepted, and the

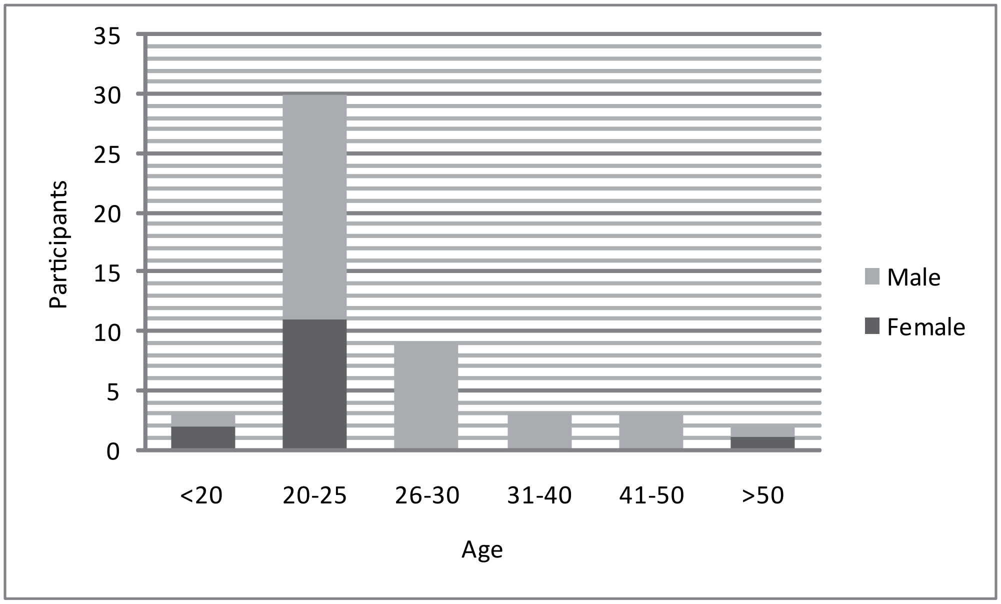


Figure 5.1: Participant age distribution.

experimenting took place in the exact same environment as the friendly scenario. One of these were selected to play the victim, while the others were assigned the task of attacking (imitating).

For the long-term hostile scenario, only two subjects participated: the victim from the previous scenario, and one attacker. This part of the experimenting took place at two locations, both at NTNU and HiG.

The friendly scenario lasted for one week, and the short-term hostile scenario endured for a little less than two weeks. When the latter scenario ended, the long-term hostile scenario was initiated, and this part of the experiment lasted for about six weeks.

5.4 Data collection

This section describes in more detail how each scenario in the experiment was carried out. Results and analysis will be presented in the proceeding chapters.

5.4.1 The Friendly Scenario

The friendly scenario was conducted indoors at HiG, on 20.5 meters of solid surface floor. Each of the 50 test subjects attended only once, providing one GO consisting of 10 WALKS each. The MR100 sensor was attached to the hip, as discussed in Section 4.2. In all cases the device was oriented the same way and fixed so that it could not move during the GO. Only one of the test subjects reported that hip attachment was problematic to him because the sensor disrupted his natural arm swing.

The test subjects were given the following task:

1. Stand still for 3-5 seconds.
2. Walk the selected walking distance in a normal way.
3. Stop and stand still for 3-5 seconds.
4. Turn around.
5. Stand still for 3-5 seconds.
6. Walk back to the starting point.
7. Stop and stand still for 3-5 seconds.
8. Turn around.
9. Repeat from the top of this list until ten WALKS have been collected.

Every test subject successfully completed these tasks, and delivered valid gait data for one GO each. Enrolling one person took about 15 minutes in total, including the paperwork.

While walking, the test subjects were also filmed. A camera mounted on a tripod first filmed the subjects from the side for two WALKS, including the turn such that both sideway directions were covered. Next, video capturing was also performed from the front and back of the subjects.

5.4.2 The Short-Term Hostile Scenario

Based on several factors, one victim and six attackers were selected for this scenario. Criteria were motivation, interest, low intra standard deviation (i.e. how stable a person walks) and initial distance to the victim. More specifically about the latter; the group of attackers both contained people walking similar to the victim, and people walking quite differently.

Each attacker were scheduled for five sessions lasting about an hour each, so this was a lot more time-consuming than the previous scenario. This is the main experiment of the thesis, and it is partly what distinguishes this work from that of Gafurov [25, 26, 18] and Stang [53], as discussed in Chapter 3. Gafurov explicitly stated that his spoof attempts were of a minimum-effort nature, involving a couple of WALKS per person and no feedback. Stang's attempt took more time, but only constituted about 15 minutes of walking per person. The short-term hostile scenario in this thesis typically involved **five hours** of work (walking + training) for each participant. This gave the analysis a much more extensive fundament of data.

In each session, video clips of the attacker's imitation attempts were shown, possible improvements were discussed and new attempts were made. A normal GO for this scenario looked like this:

1. Stand still for 3-5 seconds.
2. Walk the selected walking distance in a normal way.
3. Stop and stand still for 3-5 seconds.
4. Turn around, and wait for any oral instructions.
5. Stand still for 3-5 seconds.
6. Walk back to the starting point.
7. Stop and stand still for 3-5 seconds.
8. Turn around, and wait for any oral instructions.
9. Repeat from the top of this list until four or six WALKS have been collected.

These GOs were also video taped, but angles were changed according to the attackers interests and needs. In essence, it was not the intention to treat every attacker equally - but rather to provide the best tailored training and feedback for each one. Different individuals looked at different things on the tapes, asked different questions and found their own ways of approaching a lot of the challenges that arose.

While the previous scenario only required one GO from each test subject, this scenario required three GOs in each of the five sessions. Training of the subjects took place between each GO, as statistical reports and video takes provided updated feedback. Distance scores were presented after each GO, and the author helped test subjects come up with clever ways of mimicking, and to trash misleading clues.

The following explains the general structure of the sessions, but for some participants the session descriptions overlapped or slightly changed.

Session one and two focused on the high-level information, such as sideways posture and arm swing. The speed of walking (correlated with CYCLE length) were also evaluated and adjusted to better match that of the victim. The test subjects found arm swing and posture rather easy to extract and compare, and it proved to be possible to adapt to these high-level gait properties to some extent.

Session three included a meeting between the victim and the attacker. This way, the attacker got the chance to perform a ”live” imitation attempt (exactly as done in [25, 26]), with the victim walking in front of him during one GO. Video takes from these sessions were studied in great detail, and all participants thought these were valuable. Actually, the video became much more important than the live attempt itself; walking with the attacker provided speed and step synchronization, but did not seem to cause significant improvements itself. Some more advanced details were also looked at for some test subjects during this session.

Session four was devoted to the finer details of the gait imitation. Positioning of the feet, ankle / heel / toe dynamics, hip / torso movement and shoulder stability are examples of such details. This session contained the hardest tasks of the imitation - some clues seemed virtually impossible to pursue, while others lead to small improvements.

Session five was the final one, and at this session the participant got little or no instructions. The idea was that the attacker, with all previous training as basis, decision on how to proceed and conclude the final imitation trial. All the recorded data was available, and statistical feedback was indeed given between GOs, but how to perform the actual walking was completely left to the participant.

5.4.3 The Long-Term Hostile Scenario

The long-term hostile scenario was more loosely defined than the other scenarios. As only one attacker participated it was more convenient to be able to deviate from it, getting the best tailored training program possible. During the previous scenarios the author obtained insight in the process of recording and mimicking gait, so the long-term scenario was conducted much more efficiently than the others.

The total number of GOs for this scenario was 60, and 168 WALKS were collected in total. The total time span for the data collection was about 6 weeks, with about 10 hours of training and experimenting per week. With vast amounts of video clips available, a lot of time was devoted to digging into the details of the victim's gait. Previously successful attempts were copied and tried, and the attacker also had the time to try different shoes, floor surfaces, ground elevation levels, clothes, and even backpacks, at different times during the day.

In total for this scenario, about 60 hours were spent on training and collecting gait data alone.

Chapter 6

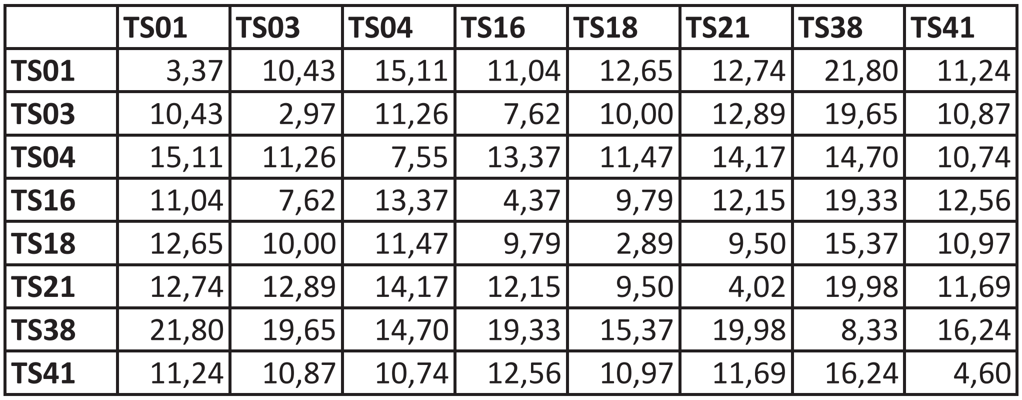
Experiment Results

This chapter will present high-level results, experiences during the experiment execution and discuss the findings. For complete data sets see Appendix A.

6.1 The Friendly Scenario

During the friendly scenario 50 participants submitted gait data, and ten templates were created for each participant. These templates represent different possible enrollments, or trials for authentication. By comparing templates we can get a picture of how well the software tool is performing.

The test subjects were given an alias *TSxx* where xx is a number in the range $[01, 50]$. Table 6.1 shows an extraction of the average DTW distance matrix in Appendix A, and provides an example of interesting results that can be presented in a straightforward way. The rows and columns consist of participants, in this case it contains those who participated in both friendly and hostile scenarios.

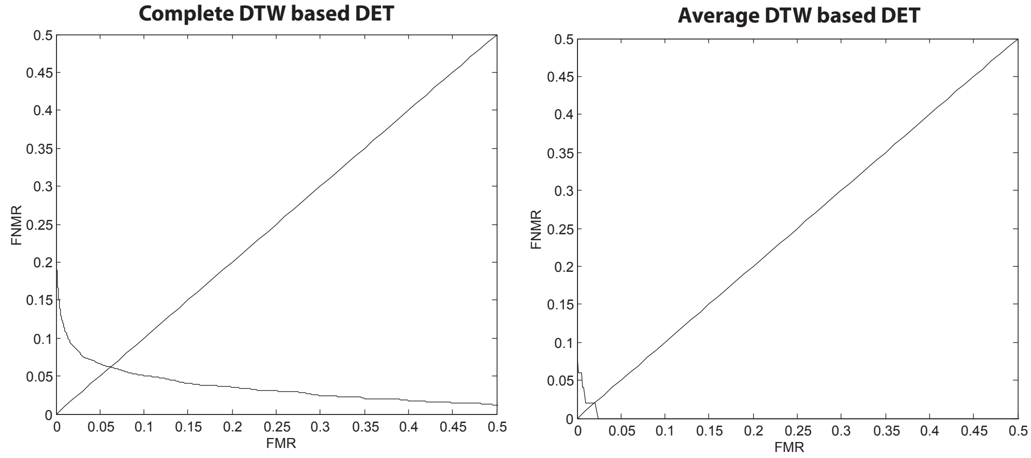


	TS01	TS03	TS04	TS16	TS18	TS21	TS38	TS41
TS01	3,37	10,43	15,11	11,04	12,65	12,74	21,80	11,24
TS03	10,43	2,97	11,26	7,62	10,00	12,89	19,65	10,87
TS04	15,11	11,26	7,55	13,37	11,47	14,17	14,70	10,74
TS16	11,04	7,62	13,37	4,37	9,79	12,15	19,33	12,56
TS18	12,65	10,00	11,47	9,79	2,89	9,50	15,37	10,97
TS21	12,74	12,89	14,17	12,15	9,50	4,02	19,98	11,69
TS38	21,80	19,65	14,70	19,33	15,37	19,98	8,33	16,24
TS41	11,24	10,87	10,74	12,56	10,97	11,69	16,24	4,60

Table 6.1: Average DTW distance matrix (extract). A cell inn the matrix provides the average DTW distance between two participants. The matrix is symmetric, as both the rows and columns represent the same set of participants. Hence, the diagonal represent (average) genuine trials.

Figure 6.1 shows two DET curves. The first one, to the left, is the main DET curve based on every possible combination when comparing templates. The DET curve to the right is based on average DTW distance scores; by evaluating each person's average intra-class DTW distance, to every other. In other words, the latter DET curve shows how verification performs for each person, both genuinely and fraudulent, on *average*.

Even though optimizing the performance of the gait analysis is not an objective for this thesis, it certainly is interesting to evaluate it. Also, it is absolutely necessary in order to be able to evaluate how well the attackers in the hostile scenario are mimicking.


Complete DTW based DET

Average DTW based DET

Figure 6.1: Complete and average DTW based DET curve. Left: DET curve from the friendly scenario, EER = 6.2%, this is the main DET curve used in this thesis, and the threshold corresponding to this EER is 8.6449. Right: DET curve based on average DTW distances, EER = 1.92%.

As described in Section 2.5, the Equal Error Rate (EER) is frequently used as a measurement of biometric system performance. Further, Table 3.1 shows different achievements in the field of gait biometrics - the best performance seen so far is around 2%, while other results range up to 20% for wearable sensors, and way higher for other gait collectors.

The collected data, including the average DTW distance matrix, can be found in Appendix A. The comparisons were made using all of 500 templates, which constitutes 124750 comparisons, whereof 2250 are genuine and 122500 are impostor trials. The EER achieved for all combinations was 6.2%, while the average DTW comparisons resulted in 1.92%. The former EER is the main result, with a corresponding threshold of 8.6449. This is the acceptance threshold that the attacking participants need to beat.

Even though DTW is the chosen metric for this thesis, it is interesting to look at some alternatives in order to confirm our assumption that DTW is superior. Figure 6.2 shows two alternative DET curves, the left one based on Euclidean distance, and the right one using Manhattan / City block distance (see Equation 3.6 and 3.5).

The EERs in these cases were 6.5% and 6.2%, respectively, so it seems the metrics are all close[1].

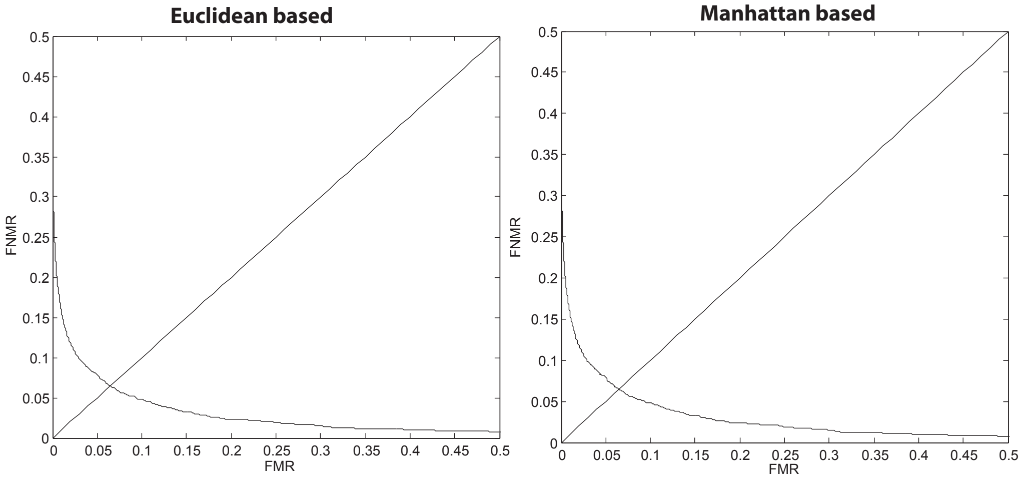


Figure 6.2: DET curve for alternative distance metrics. Left: DET curve based on Euclidean distance, EER = 6.5%. Right: DET curve based on Manhattan / City Block distance, EER = 6.2%.

These results are more than satisfactory, especially as the performance is not the main focus of the thesis. With the successful analysis of the gait data from the friendly scenario, we can move on to the hostile counterparts.

6.2 The Short-Term Hostile Scenario

As previously stated, the short-term hostile scenario constitutes the main part of the experiment, and the full data set is found in Appendix A. The six attacking participants were extensively trained for 5×45 minutes or more, **individually**, and were each given extensive feedback from several sources of information. The participants reacted to feedback and instructions differently, and were therefore trained in unequal ways in order to achieve maximum performance. This rather high amount of training effort distinguishes the experiment from previous research.

Each of the participants also attended the initial experiment, hence their first average distances to the victim were known. The distance from a participant to the victim recorded in the friendly scenario, will be referred to as the *initial* DTW distance. Further, since attackers correspond to test subjects in the friendly scenario, an ”A” will be used in addition to their original number. Hence, the six attackers A03, A04, A18, A21, A38 and A41, correspond to TS03, TS04 and so on.

The participant subject to mimicking, previously known as TS16, will now only be referred to as the *victim*. The victim was employed at HiG during the execution of the experiment, a 41 year old male. He reported no injuries affecting his gait,

[1] Appendix A contains the complete average distance matrix also for the Eucledian metric. However, the results were not very different from those based on DTW, so this metric will not get any further attention in this thesis.

and walked in a stable manner - his standard deviation, recorded during the friendly scenario, was 1.75 - well within reasonable limits. He was also highly motivated for participating, and had some previous experience which made him an excellent choice for victim.

The victim's CYCLE length for this experiment was 107.

When the friendly scenario was conducted, the victim wore a pair of gore-tex shoes. Choice of attacker footwear was subject to a lot of discussion - should the victim also ”mimic” footwear by wearing similar shoes, or should he choose a pair he feels comfortable using? There is no right and wrong to this question, but the choice fell on the latter. The attackers were required to wear the same pair of shoes for all five sessions, but he or she was free to pick any shoe type.

Table 6.2 shows some characteristics exhibited the participants, and the following sections will provide a walk-through of the experiment with each of the attackers.

Attacker	**Victim**	**A01**	**A03**	**A04**	**A18**	**A21**	**A38**	**A41**
Alias	TS16	TS01	TS03	TS04	TS18	TS21	TS38	TS41
Gender	M	M	M	M	M	M	F	M
Age	41	25	22	25	29	46	52	22
Weight	95	80	90	110	90	80	70	60
Height	180	187	173	187	190	176	168	180
DTW	4.37	11.04	7.62	13.4	9.79	12.2	19.3	12.6
STD	1.75	1.36	0.75	1.69	1.18	1.69	4.83	1.86
CLA	107	108.5	107.5	108.1	106.8	110.8	106.3	110.1

Table 6.2: Hostile experiment participants and their characteristics. CLA = CYCLE Length Average, DTW = initial DTW distance, STD = intra standard deviation. The weight is rounded to the nearest five, and measured in KG, height in CM.

The reader should note that the main analysis and the statistical results will be presented in Chapter 7. This chapter is merely presenting the results, but will still comment on the first impressions of learning.

6.2.1 Attacker A03

Attacker A03, a 22 year old male, was a student at HiG when the experiment was conducted. He reported no injuries affecting his gait, and was wearing the same shoes for all sessions - a pair perceived as a crossing between heavy winter shoes and skating / hip-hop shoes. He was initially picked due to his very low initial DTW distance, which will be discussed shortly.

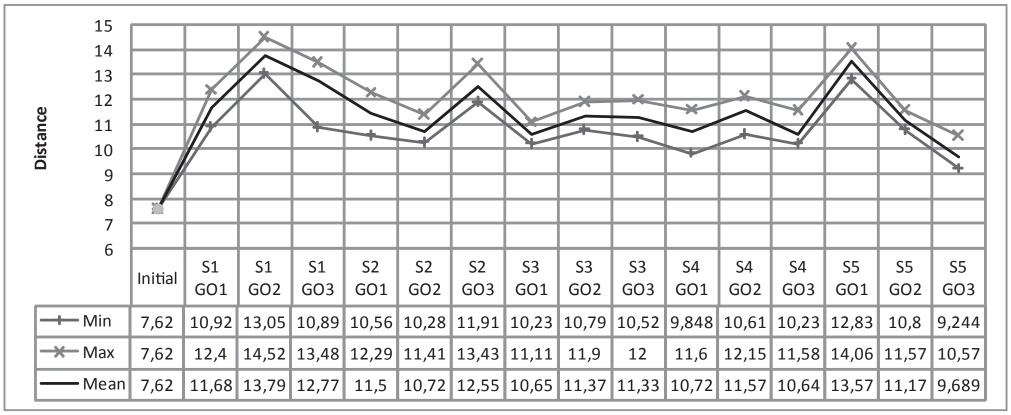
Looking at the averages, this attacker did not seem to learn anything during the experiment. The participant was able to adopt gait characteristics that did not belong to his own walking, even in a stable way, but it did not seem to get him anywhere.

The *initial* DTW distance for this attacker was very low: 7.62, with standard deviation of 0.75. These are values that even as-is seem disturbingly low compared to the victim's average intra DTW score (4.4). Hence, this attacker was candidate to providing indicators on how similar walks can be altered to match.

The CYCLE length[2] of this test subject was very close to that of victim at all times (mostly in the interval $[105, 110]$ with an overall average of 107.5), and will not be subject to discussion in this section.

During the first session, A03 first spent some time watching videos of the victim, which he compared to video clips of himself. He immediately discovered that his general body posture and arm swing were different from those of the victim. First of all A03 was walking less upright than the victim, and his arm swing came from the elbow rather than the shoulder. Hence, the first session consisted of attempts to adjust these high-level observations. The corresponding DTW scores were significantly higher than that of the initial distance, first increasing to 12.4 and then to 13.8.

After the first two GOs, videos were closely studied to spot differences. However, no apparent reason existed to explain the bad performance. Going back to natural walk did not help much either, the score still landed at 12.7 for this session.



	Initial	S1 GO1	S1 GO2	S1 GO3	S2 GO1	S2 GO2	S2 GO3	S3 GO1	S3 GO2	S3 GO3	S4 GO1	S4 GO2	S4 GO3	S5 GO1	S5 GO2	S5 GO3
Min	7,62	10,92	13,05	10,89	10,56	10,28	11,91	10,23	10,79	10,52	9,848	10,61	10,23	12,83	10,8	9,244
Max	7,62	12,4	14,52	13,48	12,29	11,41	13,43	11,11	11,9	12	11,6	12,15	11,58	14,06	11,57	10,57
Mean	7,62	11,68	13,79	12,77	11,5	10,72	12,55	10,65	11,37	11,33	10,72	11,57	10,64	13,57	11,17	9,689

Figure 6.3: Attacker A03 mimicking results. The plot shows the minimum, maximum and mean values achieved for three GOs (GO1, GO2, GO3) over five sessions (S1, S2,...). As for all distance scores, lower results are better for the attacker. In this particular case we can see a very low initial value that is never achieved during the training. Three maxima indicate points in time where new gait characteristics have just been introduced, or old ones modified. Overall, the test subject experienced little or no effect from the training.

The second session started with another attempt of normal walk, yielding scores around $10 - 12$. This was hardly an improvement, and still far from the initial value. It could seem as A03 had walked in a special (but stable) way during the

[2] The term "CYCLE length" was not used in the beginning of the experiment. For simplicity, "walking speed" was used instead, but in this context that term is a bit inaccurate. If the CYCLE length is high, then the CYCLES last for a longer period of time. Although long "leaping" steps could both have a high CYCLE length AND speed, the high length estimate will be assumed to indicate slow walk. The test subjects were informed of this interpretation, and thus had the option to either try modifying the walking speed, or the duration of their steps themselves.

friendly scenario, perhaps due to the context of being measured and filmed for the first time. Session one was a week later than the friendly scenario, so remembering details about the initial walking was difficult for the attacker.

More modest adjustments to high-level gait characteristics were made, such as slightly raising the chin (i.e. making the posture more upright), and this seemed to account for a slight improvement, to 10.7. However, once the arm swing was attempted on top of this, the average score rose again, to 12.6.

The third session did not help either. The victim was present during the first GO, and thus walked in front of A03 during this time. The GO averaged to 10.6, which was actually the best value obtained so far. Apparently, walking behind the victim indeed provided some information, the attacker reported that the arm swing was easy to adopt this way. It also seems pace and posture is affected.

More importantly, the video clips of A03 and the victim walking together were studied in great detail, and it was easy to spot previously undetected differences this way. Shoulder movement was pointed out as a big difference, A03 had a way of moving his shoulders from side to side, while the victim seemed to swing them back and forth. More trials were conducted to adjust this, and general posture, but the DTW scores rose again to 11.3 and 11.4.

For the fourth session, it was suggested that a method to adopt the shoulder swing of the victim was applied. By not only swinging the arms, but also by stretching them over to the opposite pocket, and slightly tapping it, the shoulders also had to rotate. For one GO, including different adjustments to this method, an average of 10.7 was achieved. Some WALKS were down to 9.8. However, the scores had high variance, and the attacker suggested that his next two trials consisted of normal walk. For this, averages of 11.6 and 10.6 were achieved.

The last session was almost instruction-free in order to let the attacker perform the mimicking exactly the way he wanted to himself. He chose to return to watching initial videos of the victim, and tried again to adopt high-level characteristics like arm swing and posture. The averages became 13.6, 11.2 and 9.9.

In all, there is no clear progress (negative trend) in the data collected for A03, and no distance scores stand out as exceptional - except from the initial DTW distance. Session three and four seems to be the ones with the highest and most stable performance, but the average values are all about four points higher than the initial distance. The only extrema encountered during sessions are maxima, some relating to learning new gait characteristics, and some relating to several changes to the walking, made simultaneously.

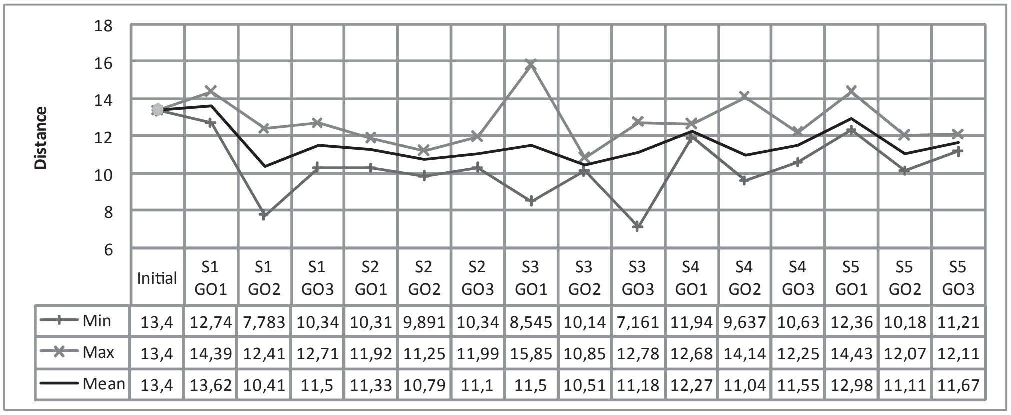
6.2.2 Attacker A04

Attacker A04, a 25 year old male, was also a student at HiG when the experiment was conducted. He reported no injuries affecting his gait, and was wearing the same shoes for all sessions - a pair hip-hop / skating shoes, somewhat heavy. Initially, A04's DTW distance was a little high: 13.4 with a standard deviation of 1.69. Although much higher distances were observed also, it made him a good candidate. The low standard deviation made A04 an even better choice.

Overall, A04 had one early improvement, but after this point his average distance curve stabilized around the overall average 11.4. The participant expressed that after the first improvement, he could not do anything to change the gait to better or worse, a statement supported by the plot.

The cycle length of A04 was unproblematic, with an overall average of 108.1. Some adjustments were made to this factor during some sessions, but the main focus was elsewhere.

The first session concentrated on the high-level details, as planned. The arm swing became the first area of focus - while the victim was moving the whole arm, using the shoulder as the main rotation point, the attacker normally walked with the elbow as the main rotation point. Changing this was difficult according to the attacker, the first attempt gave no improvements. He continued for a second GO, also slowing down a little, but mainly focusing on his arms. He attempted to make them ”stiffer” in the sense that the elbow should be prone to less rotation. The first WALK showed problems adopting this, the test subject completely changed his gait: the right foot stride was now accompanied by the right arm moving in the same direction (also called ”pace”, or ”passgang” in Norwegian). As this is not a common way of walking it seems the gait adjustments at this point interfered too much with natural moves.



	Initial	S1 GO1	S1 GO2	S1 GO3	S2 GO1	S2 GO2	S2 GO3	S3 GO1	S3 GO2	S3 GO3	S4 GO1	S4 GO2	S4 GO3	S5 GO1	S5 GO2	S5 GO3
Min	13,4	12,74	7,783	10,34	10,31	9,891	10,34	8,545	10,14	7,161	11,94	9,637	10,63	12,36	10,18	11,21
Max	13,4	14,39	12,41	12,71	11,92	11,25	11,99	15,85	10,85	12,78	12,68	14,14	12,25	14,43	12,07	12,11
Mean	13,4	13,62	10,41	11,5	11,33	10,79	11,1	11,5	10,51	11,18	12,27	11,04	11,55	12,98	11,11	11,67

Figure 6.4: Attacker A04 mimicking results. The plot shows the minimum, maximum and mean values achieved for three GOs (GO1, GO2, GO3) over five sessions (S1, S2,...). As for all distance scores, lower results are better for the attacker. In this particular case we can see an early drop in the distance, to a level that stabilizes for the rest of the training. However, no further improvements are clear from the data, in general the average is very stable around 11.4. One peak shows a clear change in A04's gait characteristics, that he first has trouble adapting to, but the average remains the same. Overall, the test subject experienced little or no effect from the training, except from the early improvement.

However, once A04 realized that the walk was off, he chose to incorporate the mimicking more carefully during the rest of the GO, and he also attempted to adjust the speed. This resulted in an immediate drop in distance scores, the following trials averaged to 10.0 with $7, 8$ as the minimum. The results are easily spotted in Figure 6.4, as this constitutes the only drop of values - the only session with successful learning.

Session two ranged from 9.9 to 12.0, so the characteristics learned from session one seemed to endure. The subject walked reasonably stable and his CYCLE length was mostly perfect. During this session the attacker attempted to rise his chin while walking, in order to obtain the much erect posture exhibited by the victim. At some point this brought A04 some improvements, but only for one GO. Focusing on the chin later in the training gave little or no effect.

The victim attended session three, and walked with A04 for one GO. The distances recorded during this particular GO averaged to 10.5, a little better than the total average. The attacker further attempted to copy what was perceived as hip oscillations - a masculine[3] way of moving the hips.

The results from the hip movement trials were not trivial to make sense of. The distances for that particular GO was $\{15.8, 9.4, 12.2, 8.5\}$. After the second WALK, the attacker received some adjusting instructions. Hence, it might seem that the attacker first tried something new, failed, and then recovered on a second try. The same follows for WALK three and four. However, retries did not produce the same pattern, and aside from an extreme minimum of 7.1 (GO three, WALK one), the low values were never reached again from this point. The large max-peak in the plot shows how this new mimicking characteristic deviates from the rest of the data.

Despite the inconclusive results, we still saw the hip oscillations as the key to progress in the case of A04. Session four concentrated on fine-tuning details related to this gait characteristic. During the three GOs of this session, 14 WALKS were conducted only focusing on the hips. This included moving body parts that also affects the hips; one example would be shoulder movement - by tapping the fingers on the opposite pocket for each stride, the upper body rotates and the hips slightly follow. When good results were obtained, the attacker tried to reproduce the characteristics in the proceeding WALKS. Overall these attempts averaged to 11.5, pretty much like the total average of all five sessions.

Videos were frequently used as source of information during all these sessions, and for the last session the attacker wanted to see the first videos of the victim. In this session all decisions were left to A04, and he chose to look at high-level gait characteristics again. After first obtaining an average of 13.0, he proceeded to adjust posture and arm swing, finally leading to a session average of 11.9.

Overall, the test subject experiences little or no effect from the training, except from the improvement observed early in session one. For that particular session

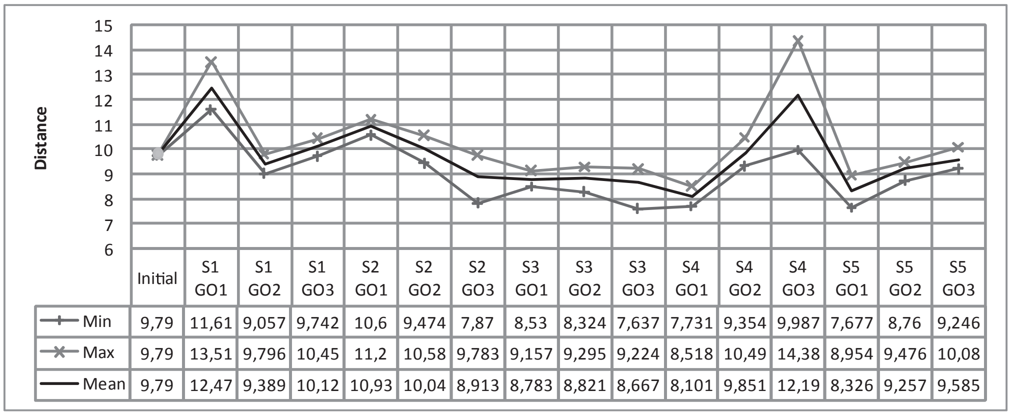
[3] The test data suggested that female participants moved their hips side to side, making the top of their hip ”bounce” upwards for each stride. Males seemed to either possess little or no (visible) hip movement, while others, like the victim, thrusted the hip forward for each stride. The victim described it as ”moving my thighs around one another, as they are rather large”.

A04 seemed to discover a general way of walking somewhat more alike the victim, and this brought him about two points closer to the victim on average. However, even though he managed to maintain the lower distance, further improvements are not identifiable. The average distance curve is very stable around 11.4, and as the attacker stated himself - it seemed like nothing could make him better or worse off once he got there.

6.2.3 Attacker A18

Attacker A18 is a 29 year old male who also studied at HiG during the experiment. He reported no injuries affecting his gait, and was wearing the same shoes for all sessions - a pair of classic ”comfort” shoes. The attacker started out with a quite low initial DTW distance, 9.79, which groups him into a category of similar walk attackers. A18 also exhibited a low standard deviation, 1.18, proving that his gait was very stable during the friendly scenario, which is a plus also.

A18 was among the better performing attackers of the group. Even with a low initial distance, the attacker seemed to learn during the first three sessions, bettering his performance in a stable manner. This can be seen in Figure 6.5. However, after a while the trend was broken, and the last two sessions yielded significantly higher values.



	Initial	S1 GO1	S1 GO2	S1 GO3	S2 GO1	S2 GO2	S2 GO3	S3 GO1	S3 GO2	S3 GO3	S4 GO1	S4 GO2	S4 GO3	S5 GO1	S5 GO2	S5 GO3
Min	9,79	11,61	9,057	9,742	10,6	9,474	7,87	8,53	8,324	7,637	7,731	9,354	9,987	7,677	8,76	9,246
Max	9,79	13,51	9,796	10,45	11,2	10,58	9,783	9,157	9,295	9,224	8,518	10,49	14,38	8,954	9,476	10,08
Mean	9,79	12,47	9,389	10,12	10,93	10,04	8,913	8,783	8,821	8,667	8,101	9,851	12,19	8,326	9,257	9,585

Figure 6.5: Attacker A18 mimicking results. The plot shows the minimum, maximum and mean values achieved for three GOs (GO1, GO2, GO3) over five sessions (S1, S2,...). As for all distance scores, lower results are better for the attacker. In this case it seems that the first three sessions really increase the performance of the attacker, the distance decreases in a stable manner. The trend is broken by the last two sessions, where the results are significantly higher.

On some occasions A18 was instructed to slow down his steps, but overall the CYCLE length of the attacker was unproblematic: the total average was 106.76. The biggest adjustment took place during the first session, where the attacker's CYCLE length was down to 100. The quick pace probably explains why the first GO gave poor results, as the adjustment brought him below his initial distance immediately. Posture and arm swing was also a main focus area during this session.

In all the performance increased compared to the very first GO, but were still close to the initial distance. The average values for this session were $\{12.5, 9.4, 10.1\}$.

A18 continued in the second session by trying to rise his chin while walking, in order to obtain an erect posture. Trying this was fruitless for the first GO. The second GO was conducted in collaboration with the victim. The attacker expressed that watching the upper body of the victim during the walk gave him an advantage, and the DTW decreased slightly. After this the videos were carefully studied, and the attacker pointed out differences in the hip movement. The session ended in another decrease of distance scores, as the attacker tried to mimic the hip movement. The average for this GO was as 8.9.

The third session picked up the thread on hip movement, but also introduced attempts to position the feet in a ”V-formation” while walking. The hip movement adjustments continued to elevate performance, while the foot adjustment did not show a huge effect. The average values for this session were $\{8.8, 8.8, 8.7\}$, some improvement is present, and the performance is stable.

The fourth session started out well with a GO yielding distance scores in the range of $[7.3, 8.5]$. However, further adjustments did not have positive effects, and suddenly the distance scores were rising. The attacker failed to recall how he achieved the low scores from previous attempts, despite intensive video study. It was pointed out that his attempts to manipulate hip movement were actually having a great visible effect on the shoulders, therefore the final GO was dedicated to changing actual hip movement instead. A18 expressed that the resulting way of walking was unnatural and uncomfortable - and as the figure shows this attempt yielded very high distances.

The fifth session was for self-coaching, and the attacker tried to reproduce the original hip mimicking from session two. The DTW distance indeed decreased for the first GO of this session, but then slightly rose for each following GO: $\{8.3, 9.3, 9.6\}$.

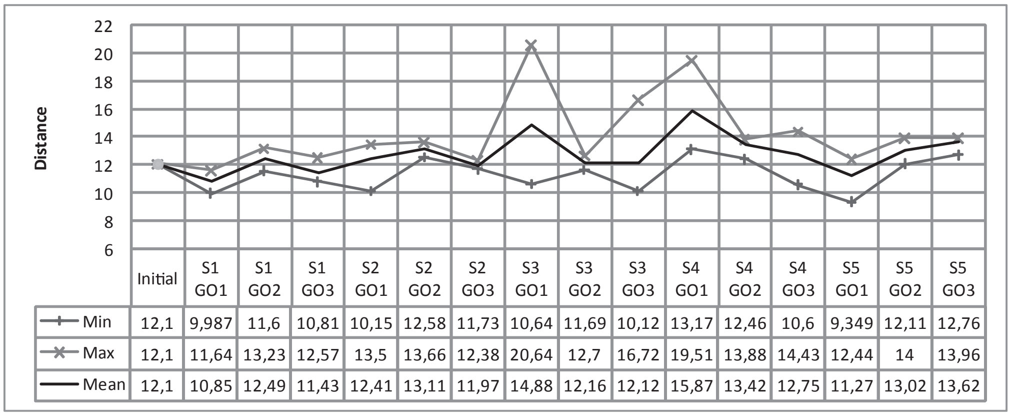
The fitted learning curve can be seen in Figure 7.4. It is clear that the first three sessions together form a decreasing trend, but it is ended by session four and five. A18 show a certain capability to learn and adopt gait characteristics, but his achievements are still limited.

For A18 the lower values could be maintained in a stable manner, but attempts to improve performance even more had only negative effects. The attacker claimed that new instructions and attempts in session four made it hard to remember the details from the three previous sessions. This might explain why the last self-coached session five was subject to worse performance than what we saw earlier.

6.2.4 Attacker A21

A21 is a 46 year old male, employed at HiG. He reported no injuries affecting his gait, and wore classic casual shoes for all sessions. This attacker initially had a DTW distance of 12.1 to the victim, with a standard deviation of 1.69. This classified A21 as an attacker having a gait somewhat similar to that of the victim, and the stability of his walk was well within acceptable limits.

As illustrated by Figure 6.6 and 7.5 no real learning took place during A21's sessions. The attacker found the whole process of changing characteristics of his gait very difficult, and added the remark ”I am not a dancer”. His inability to adopt gait features were clearly visible during the sessions, most adjustments altered the gait in its entirety, and changed it into an unnatural and unstable pace. The attacker stated that he was also uncomfortable with the positioning of the MR100.



	Initial	S1 GO1	S1 GO2	S1 GO3	S2 GO1	S2 GO2	S2 GO3	S3 GO1	S3 GO2	S3 GO3	S4 GO1	S4 GO2	S4 GO3	S5 GO1	S5 GO2	S5 GO3
—+— Min	12,1	9,987	11,6	10,81	10,15	12,58	11,73	10,64	11,69	10,12	13,17	12,46	10,6	9,349	12,11	12,76
—×— Max	12,1	11,64	13,23	12,57	13,5	13,66	12,38	20,64	12,7	16,72	19,51	13,88	14,43	12,44	14	13,96
—— Mean	12,1	10,85	12,49	11,43	12,41	13,11	11,97	14,88	12,16	12,12	15,87	13,42	12,75	11,27	13,02	13,62

Figure 6.6: Attacker A21 mimicking results. The plot shows the minimum, maximum and mean values achieved for three GOs (GO1, GO2, GO3) over five sessions (S1, S2,...). As for all distance scores, lower results are better for the attacker. In this case we see a very flat trend, indicating that no learning took place. The large difference between the maximum and minimum for certain GOs occurred when new characteristics were introduced, the attacker did not feel comfortable adopting them and his gait became less natural.

The first session was dedicated to the high-level characteristics of the gait, and A21 pointed out that he thought he already walked somewhat similar to the victim. Although this was not technically true, the attacker's posture was indeed a characteristic to keep unchanged. The arm swing was adopted, but the attacker felt that it was unnatural, the GOs yielded $\{10.9, 12.5, 11.4\}$ on average; no results were conclusive. Underway some attempts were made to decrease the CYCLE length of the attacker, as it had an average of 114.5 during this session.

The ”V-formation” of the feet was pointed out by A21 as a possible difference factor, and the second session thus started out with this change in mind. The results hardly changed, and the attacker felt that the walk became unnatural. The CYCLE length was still too high. The second GO was done in collaboration with the victim, who walked in front of him as usual. This corrected the CYCLE length issue, but increased the distance significantly, to 13.1. The videos from this GO was studied, and an attempt was made to rotate the upper body while walking. This was perceived as highly unnatural for A21, and the distance score remained high.

The third session started out by trying to focus on the upper body rotation again. Again the walk became unnatural, and the CYCLE length increased to an average of 119.3 for this session. The first GO yielded values of huge variance, ranging from 10 to more than 20. This was obviously the wrong path to take. Next the attacker attempted to adjust hip movement, but also this was uncomfortable. The upper body movement was still considered to be an important adjustment, so the attacker suggested a different way of achieving this: by tapping the hand on the opposite pocket for each step. This did not change anything significantly.

The fourth session was also devoted to upper body movement, but results worsened - the attacker did not feel comfortable with any changes of this kind.

For the last session, where the attacker chose his own moves entirely, he decided to concentrate on speed. The results did not change significantly, and the total session average became 12.6.

A21 found it particularly difficult to change his manner of walking, and it is clear from the results that no learning took place. The fitted learning curve in Figure 7.5 rather shows *increasing* distance. It is interesting to see how different individuals have unequal fundamental abilities that can help them manipulate their own gait, and it is clear that choosing attackers based on such abilities would have been advantageous. However, A21 was the only participant reporting these difficulties.

6.2.5 Attacker A38

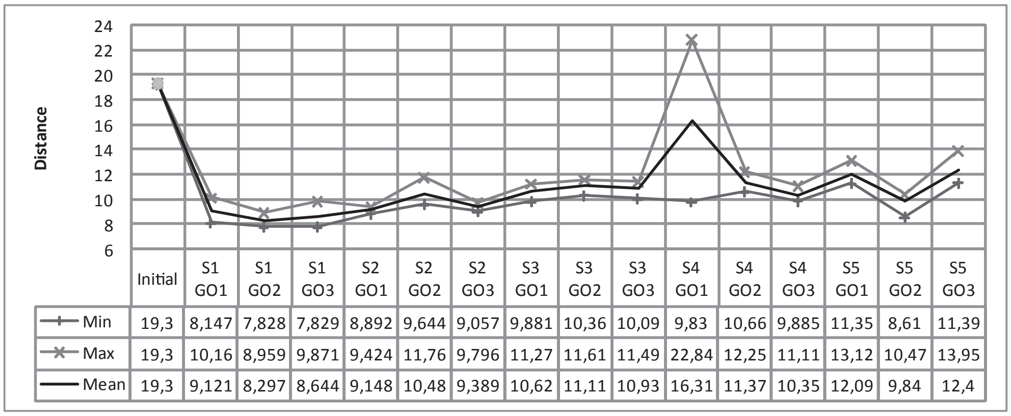
A38 was the attacking group's only female participant, 52 years of age and also employed at HiG. She reported no injuries affecting her gait, and was wearing a somewhat heavy pair of women's shoes for all five sessions. A38 was selected for many reasons. First of all she has a very high initial DTW distance to the victim: 19.3, which constitutes the highest initial distance in the group. Looking at her performance in the friendly scenario however, we can see that her standard deviation was also quite high, 4.83, so we cannot be sure is the measure is precise, but it is still interesting to let her have the role as a high distance attacker. Secondly, she was highly motivated for participating, even after warnings of the effort needed from her part.

Gafurov et. al found indicators that suggested that mimicking is affected by gender [18]. According to his conclusions it is an advantage to pick a target of the same gender when trying to mimic, but as we shall see her performance was not very different from the male ones, and she definitely did better than, say, A21.

The overall results, illustrated in Figure 6.7 and 7.6, show that also A38's learning curve is upward-sloping. However, she did do a giant distance leap on the very first session, from the initial 19.3 to a session average of 8.7.

Cycle length, or walking speed, was not a big issue for this attacker. In the beginning she was instructed to slightly speed up her pace, but her total average var 106.3, only 0.7 samples from that of the victim.

The first session concentrated on posture and arm swing, and this was when she managed to decrease her distance from 19.3 to an incredible 8.7. This is a vast



	Initial	S1 GO1	S1 GO2	S1 GO3	S2 GO1	S2 GO2	S2 GO3	S3 GO1	S3 GO2	S3 GO3	S4 GO1	S4 GO2	S4 GO3	S5 GO1	S5 GO2	S5 GO3
Min	19,3	8,147	7,828	7,829	8,892	9,644	9,057	9,881	10,36	10,09	9,83	10,66	9,885	11,35	8,61	11,39
Max	19,3	10,16	8,959	9,871	9,424	11,76	9,796	11,27	11,61	11,49	22,84	12,25	11,11	13,12	10,47	13,95
Mean	19,3	9,121	8,297	8,644	9,148	10,48	9,389	10,62	11,11	10,93	16,31	11,37	10,35	12,09	9,84	12,4

Figure 6.7: Attacker A38 mimicking results. The plot shows the minimum, maximum and mean values achieved for three GOs (GO1, GO2, GO3) over five sessions (S1, S2,...). As for all distance scores, lower results are better for the attacker. This attacker had a vast improvement in the beginning, but failed to improve after this point. A slightly increasing trend can be identified, but it is not very significant. The large extrema in the fourth session indicate new instructions and characteristics that did not work well for the attacker.

improvement from the initial distance, and even more alarming - her gait was stable. She tried to further change smaller details in hip movement, without much effect, but her high performance persisted. On some occasions she managed to get scores below 8.

The second session concentrated much on the same things as the first, but now feet adjustments were also made, along with further hip movement attempts. She pointed out that her feminine way of moving her hips was clearly different from what could be seen on the video of the victim. Results were stable, though a bit higher than for the previous session, the session average was 9.7.

The victim attended the third session, walking next to him brought A38's distance score up to an average of 10.6. This decrease in performance persisted throughout the session, even though videos from all previous GOs were extensively studied. Rotating the upper part of the body was one of the characteristics that were attempted during this session. The session average was 10.9, and overall the results were still very stable.

During the first GO of session four A38 attempted to do some more radical changes to her gait, basically by swinging her whole upper body from side to side. The idea was that this might bring forth more masculine hip movements: where her hips usually went up and down, his went back and forth. She abandoned the idea after only one try, and the only extrema visible in the figure shows that she probably had good reasons to. It did not work well for her to change hip movement. She spent the rest of the session trying to reconstruct the gait in session one and two. The following average values were close to 11, so the performance was still not as good as before.

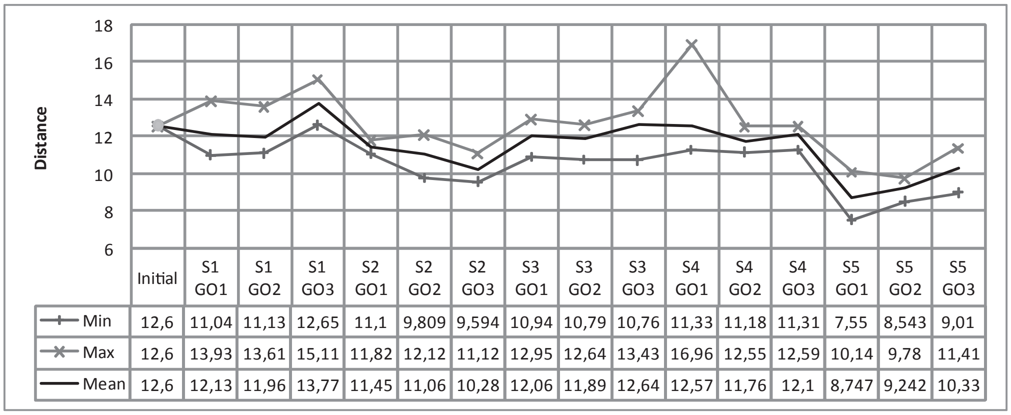
The fifth session was left entirely to her own choices. She tried normal gait with lower speed, then she tried to speed down even more, and she tried to pay attention to her shoulders. The session average was 11.4, so it seems she could not recall how she achieved the lower ones earlier.

Overall A38 was quite stable, but it was very hard for her to learn anything that clearly yielded better results. The initial value was very high, and the extreme leap in session could give the impression of A38 being a ”wolf” (i.e. a skilled impostor). However, in the end the results from the first session constituted some of the lowest results for the attacker, so no real improvement was seen after this point. Part of the reason for this can be her high standard deviation in the friendly scenario; maybe her gait was actually much closer to the victim than first assumed. If this was the case, she might never have had any improvement at all.

6.2.6 Attacker A41

A41 was a 22 year old male, also a student at HiG that reported no injuries affecting his gait. He wore the same shoes for all sessions, a pair of low key hip-hop shoes. With an initial distance of 12.6 he qualified for a similar-gait attacker, and his standard deviation was within acceptable limits for the friendly scenario, 1.86.

Looking at Figure 6.8 some improvement is visible, but it would still be risky to assume a real learning curve. The attacker felt that his improvement was non-existing, and that the fifth session was more of a random lucky shot.



	Initial	S1 GO1	S1 GO2	S1 GO3	S2 GO1	S2 GO2	S2 GO3	S3 GO1	S3 GO2	S3 GO3	S4 GO1	S4 GO2	S4 GO3	S5 GO1	S5 GO2	S5 GO3
Min	12,6	11,04	11,13	12,65	11,1	9,809	9,594	10,94	10,79	10,76	11,33	11,18	11,31	7,55	8,543	9,01
Max	12,6	13,93	13,61	15,11	11,82	12,12	11,12	12,95	12,64	13,43	16,96	12,55	12,59	10,14	9,78	11,41
Mean	12,6	12,13	11,96	13,77	11,45	11,06	10,28	12,06	11,89	12,64	12,57	11,76	12,1	8,747	9,242	10,33

Figure 6.8: Attacker A41 mimicking results. The plot shows the minimum, maximum and mean values achieved for three GOs (GO1, GO2, GO3) over five sessions (S1, S2,...). As for all distance scores, lower results are better for the attacker. The graphs are quite flat, even though some improvement can be identified, it is hardly enough to call it learning.

The first session became subject to speed adjustment. Arm swing was also introduced. This did not go extremely well, the session average was just above the initial distance. However, a session minimum average of 12 was achieved. The higher results actually seemed to appear when the speed was adjusted, so this was noted for the next session - the speed of A41 should not be changed from normal.

The second session started with trials of normal gait (and speed), only modifying it by adding a subtle arm swing. This did not change much. Further the attacker attempted to ”stiffen” his arms, and swing them in a more robot-like fashion, which we hoped would result in what the victim himself described as his characteristic ”gorilla walk”. However, no significant changes to the distance scores were observed. Finally for this session, we focused on posture. By lifting the chin the distance decreased to an average of 10.3, despite the fact that this characteristic seemed a bit unnatural to the attacker. Lifting the chin resulted in a more erect posture, which the victim exhibits as one of his main gait characteristics. The third session was conducted in cooperation with the victim, walking together resulted in an average of 12.1. All videos were studied, and further attempts were made to adopt gait characteristics, while still preserving the raised chin from session two. However, the results did not change much, and all remained close to 12. Finally hip movement and arm swing were tried simultaneously, increasing the average distance to 12.6.

The fourth session concentrated a lot on video, and arm swing was put to further tests, along with movement of the entire upper body. The session average became 12.2, at this time it seemed like the attacker was stuck - nothing made the gait better or worse.

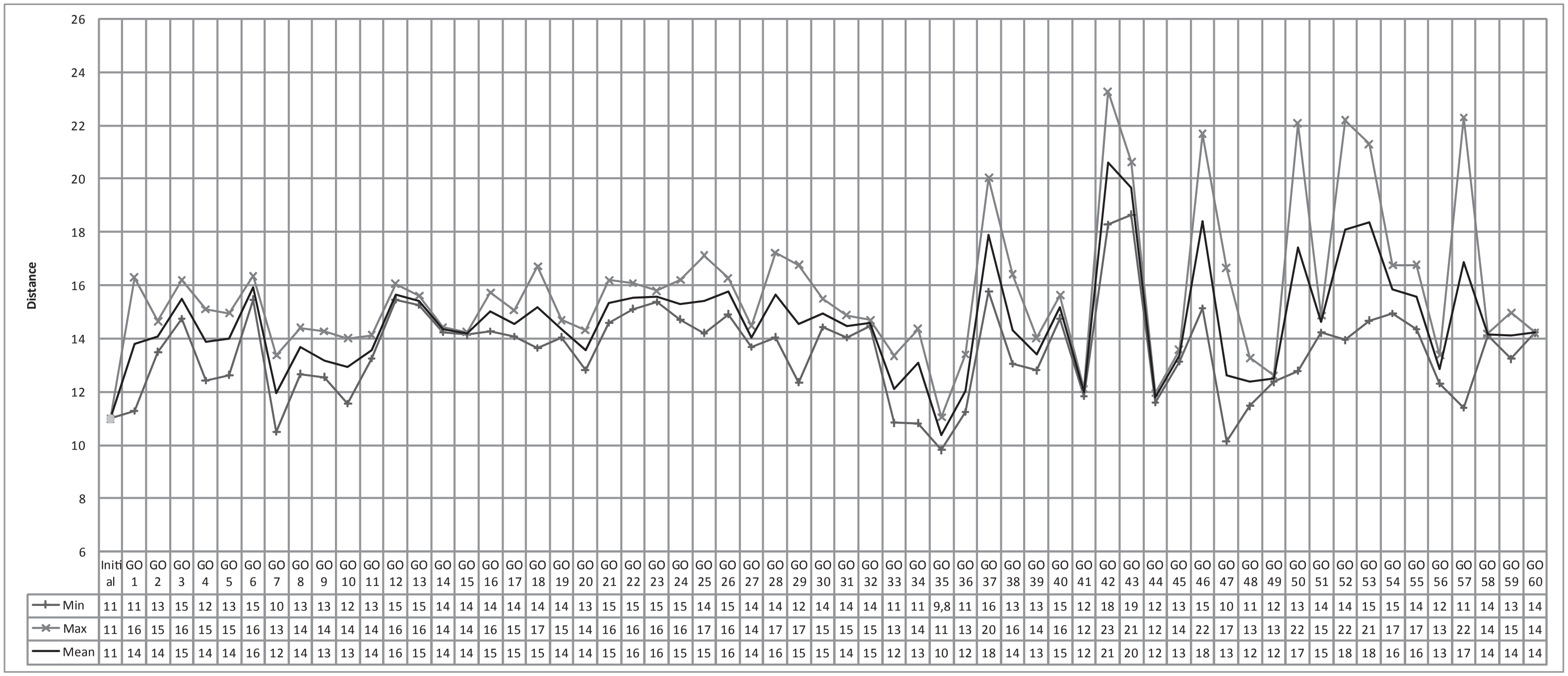
Over the first four sessions the attacker seemed a bit disappointed that he could not decrease his scores. However, the first GO for the fifth session plunged down to an average of 8.7. This really enthused A41, and with renewed energy he tried again, mostly focusing on posture, now obtaining the averages 9.2 and 10.3.

The fifth session appears to be an outlier, especially for the first GO, but can also be seen as part of a decreasing trend. Figure 7.7 shows the learning curve, and it should be noted that the local minima indeed get lower and lower. However, actually recognizing it as learning might be to go too far, by following the figure step by step one can easily see that without the outlier in the fifth session the curve is very flat. The analysis will continue in the next chapter.

6.2.7 Summary

No radical improvements have been observed in the performance of any short-term attack participants. By first impression this is especially clear in the case of the attackers A03, A04, A21 and A38, though the real discoveries are left for the next chapter.

For some attackers we can see improvements from the initial distance scores, but



	Initial	GO 1	GO 2	GO 3	GO 4	GO 5	GO 6	GO 7	GO 8	GO 9	GO 10	GO 11	GO 12	GO 13	GO 14	GO 15	GO 16	GO 17	GO 18	GO 19	GO 20
Min	11	11	13	15	12	13	15	10	13	13	12	13	15	15	14	14	14	14	14	14	13
Max	11	16	15	16	15	15	16	13	14	14	14	14	16	16	14	14	16	15	17	15	14
Mean	11	14	14	15	14	14	16	12	14	13	13	14	16	15	14	14	15	15	15	14	14

	GO 21	GO 22	GO 23	GO 24	GO 25	GO 26	GO 27	GO 28	GO 29	GO 30	GO 31	GO 32	GO 33	GO 34	GO 35	GO 36	GO 37	GO 38	GO 39	GO 40
Min	15	15	15	15	14	15	14	14	12	14	14	14	11	11	9,8	11	16	13	13	15
Max	16	16	16	16	17	16	14	17	17	15	15	15	13	14	11	13	20	16	14	16
Mean	15	16	16	15	15	16	14	16	15	15	14	15	12	13	10	12	18	14	13	15

	GO 41	GO 42	GO 43	GO 44	GO 45	GO 46	GO 47	GO 48	GO 49	GO 50	GO 51	GO 52	GO 53	GO 54	GO 55	GO 56	GO 57	GO 58	GO 59	GO 60
Min	12	18	19	12	13	15	10	11	12	13	14	14	15	15	14	12	11	14	13	14
Max	12	23	21	12	14	22	17	13	13	22	15	22	21	17	17	13	22	14	15	14
Mean	12	21	20	12	13	18	13	12	12	17	15	18	18	16	16	13	17	14	14	14

Figure 6.9: Long term attacker A01 mimicking results. The plot shows the minimum, maximum and mean values achieved for a number of GOs (GO1, GO2,...) and sessions (S1, S2,...). As for all distance scores, lower results are better for the attacker. Also this curve is very flat with little indications of learning.

then the results often stabilize around some value. In other cases we see that the initial distance is one of the better results, and that the rest of the training had a worsening effect on performance.

To get a better idea of how the attackers performed, a regression analysis and some further discussion is necessary. This part of the thesis is left for Chapter 7.

6.3 The Long-Term Hostile Scenario

As previously mentioned, the time span of the short-term hostile scenario could be extended to provide more accurate results, but in the context of the thesis that was not possible.

Results from a long-term experiment involving only one test subject, does not really provide statistically significant results. However, it is still interesting because during the experimenting the author obtained deep insight in the process of training gait mimicking, and also became an ”expert” on the particular gait of the victim. This is why the result from this scenario is also important.

The long-term attacker's characteristics are listed in Table 6.2, under A01, and the same rules and logic apply to this scenario except that the training process will be more free. This was explained in the experiment design chapter - Section 5.4.3.

A01 had an initial distance of 11.04, which relative to the other attackers lies somewhere in middle. A low standard deviation had been observed from the friendly scenario, 1.36, which indicates a very stable walk. This ability was probably developed during earlier testing phases not included in the report.

The results for A01 are presented in Figure 6.9. These are minimal, maximal and mean values, averaged for all the 60 GOs. In total, 168 walks were collected - significantly more than for the other attackers. Still, it is easy to see that even with this amount of training, the attacker does not gain much headway. First of all, the graph in its entirety is quite flat, with a period of high variance in the second half of the graph. Also, the initial distance lies far lower than most of the values collected.

A01 started out writing down a list of all previously observed characteristics of victim's gait, and all the different attempts to adopt these. The idea was to efficiently go through each one to see if a shortcut to better performance could be found. Gait videos of A01 and the victim were studied extensively in advance.

The first few GOs were spent on CYCLE length experimenting, combined with erect posture. Shortly after that, a few GOs were spent on arm swing and different ways of stiffening the arms. The chin was raised to different elevations, and all this was attempted at different speeds. The results were all bad compared to the initial distance. The overall average for these GOs was 14.52, significantly higher than what the friendly scenario indicated.

Some of the following GOs resulted in an improvement to an average of 12.04 altogether. This was achieved by tapping the pockets and thus moving the shoulders more, tried at different speeds and magnitudes. Some hip movement adjustment was also included here.

All of the previous characteristics were then tried with V-formation of the feet, without much improvement, and sometimes performance worsened. For a while the average seemed to stabilize around 15. This persisted also for different amounts of clothes, different shoe types and even with a backpack. Many such attempts were made to gain heavier weight without improvement. At this point A01 felt he was getting nowhere whatever he did, so he went even further to look for shortcuts - he tried walking uphill, downhill, stair cases, influenced by alcohol, late night and early morning attempts and so on. Nothing made a difference at this time.

A large improvement was achieved when attempting a new way of walking - trying not to move the upper body at all. That included not changing the elevation of the shoulders, a somewhat difficult task. With some training, the series of averages {12.10,13.10,10.37,12.04} were achieved. This made A01 believe he had a breakthrough, breaking through a natural border around 15 (more on this in Chapter 7).

The day after A01 could not reproduce the good results. However, it was interesting that the low results were so stable the day before, so he continued in the same fashion attempting variations of holding his upper body still while moving. This caused a lot of instability, which can be clearly seen in the last half of the data set. However, A01 did not want to give up on this idea. It was the only sign of learning so far, so it was logical to pursue this particular gait feature. As the figure shows, several results around 10 were achieved, but often followed by very high values, sometimes above 20.

It seemed very hard to get stable good results, and as the submission date of the thesis got closer the experiment had to end. Judging by first impression, Figure 6.9 shows very little improvement in A01's performance. The curve starts out very flat, and the deviations in the last half of the training period does not show a significant trend. The training seems to have no effect on A01 even in the long term, with an overall average of 14.55, about 3.5 points higher than the initial distance. However, these results are actually quite interesting, as further discussed in Chapter 7. The full data set can be found in Appendix A.

Chapter 7

Analysis and Discussion

This chapter provides the main analysis of the collected data, and discussions related to the findings. The most important part of this chapter is the statistical analysis, where each attacker's result is evaluated in terms of a regression model. The results from this analysis are used to answer to the initial objectives of the thesis.

7.1 The Plateau: A Limit to Learning

As the experiment was conducted, attackers felt that despite that they sometimes improved performance, they found it very hard to improve beyond a certain point. This point was different for every attacker, and it seemed like some kind of natural limit existed - on average the attacker could not break it. This limit, or plateau, will be discussed in this section.

7.1.1 Definition and Characteristics

The natural limit we are looking for will be loosely defined as a *plateau*. A plateau can be defined as ”a state or period of little or no change following a period of activity or progress” [16], so on a learning curve it would correspond to the curve flattening out. Hence, observations concentrate around some value on the Y-axis, illustrated in the left part of Figure 7.1.

If exactly one plateau exists for each individual, then the success of an attacker is **predetermined** - the plateau has to lie below or near the acceptance threshold for an impostor to ever be able to succeed. How near depends on the variance in the data.

However, the experiment did not last long enough to draw final conclusions on how future training will affect the performance. The thesis will hopefully provide valid indicators, but none of these would be as statistically significant as, say, a three or four year long training program.

The uncertainty of the future is also one of the reasons why the name ”plateau” was chosen. If a temporary plateau is reached, and the performance later increases due to an extended training period, the term still makes sense. In this case one can imagine several plateaus belonging to the same performance plot, as illustrated in the right part of Figure 7.1. This situation is also interesting, as questions arise on how to break through the different plateaus.

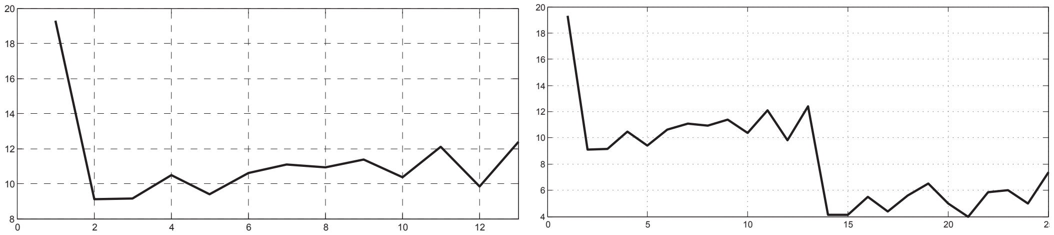


Figure 7.1: Plateaus, conceptual illustration. Left: a single plateau around 11. Right: Two plateaus, one around 11 and one around 5.

7.1.2 Finding the Plateau

Throughout the analysis plateaus of a function will be one of the main things to look for. Intuitively it can be identified by looking at points of resistance, average values and converging curves. Coefficients from fitted ”trend lines” can also be put to use for this purpose. Still, the most scientific way to find the plateau would be to look for a mathematical *limit*. The limit of a function tells us exactly where it is heading when x goes to infinity.

By now the reader might wonder what separates the plateau from a limit. What are the differences? The main difference is that a if a function exhibits a limit, only one such limit can exist. In the above it was suggested that an observed set of data points could exhibit several plateaus, and it would be interesting to see how each one could be ”broken” if this is the case.

If only one plateau exists for an attacker, then the plateau and limit are identical. If several plateaus exist, then the lowest one will equal the limit. Hence, while the limit is a purely mathematical concept that may or may not correspond to nature, the plateau opens for more human-like function behavior.

As the data set is not ”gigantic”, we shall see that working with plateaus will be very similar to working with limits.

7.2 Regression Analysis

When constructing learning curves we make approximations of the observed results. We are not interested in an expression that fits the observations perfectly (e.g. splines [8]), but rather something that would indicate a trend. In other words, we need an indicator that tells us where the results are heading - are we improving, or are we stuck?

In this thesis the main tool for analysis will be regression. Before this can be done, a model needs to be chosen. There are several models available for us to play with, and as for the choice of gait technology it is not easy to say which is best. There is no industry with vast experience in the field of gait biometrics, and these experiments have never been conducted before. Hence, the choice of model for gait analysis were one of task that inevitably emerged from this thesis.

Some intuitive choices are the linear and the logarithmic fitted curves [59, 36]. However, the approximations might not converge. Having a limit would be advantageous in order to discover plateaus - and it would better fit the structure of the data seen so far. The logarithmic model can indeed be manipulated into a convergent equation (e.g. $Y = \beta_1 + \beta_2 \ln(1 + \frac{\beta_3}{X})$), but to avoid problems with complex parameters and discontinuous curves we will base our model on an exponential curve:

$$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}, \tag{7.1}$$

where β_1, β_2 and β_3 are constants, the regression parameters[1]. In essence, this equation estimates observation i by $Y(i) = \beta_1 + \beta_2 e^{\frac{\beta_3}{i}}$. The difference between the estimated value and the actual observation is known as the *residual*. The residual for estimation i is defined as:

$$r_i = |Y(i) - f(i)|, \tag{7.2}$$

where $f(i)$ is the actual observation of i.

In Equation 7.1 we observe that β_2 and β_3 provides information about the progression of the attacker. If the two constants are both negative, or both positive, the attacker is learning (i.e. we get a downward sloping curve). If they are preceded by unequal signs, the attacker's performance is worsening. The magnitude of the constants tells us about the speed the attacker is (un)learning, or in other words how fast he is approaching his plateau. Values closer to zero mean faster progression.

Equation 7.1 forms an exponential fitted curve that converges to $\beta_1 + \beta_2$, more formally:

$$\lim_{X \to \infty} \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}. = \beta_1 + \beta_2 \tag{7.3}$$

This will be used to identify single plateaus for the participants.

In the name of quality assurance we will look at the MSE, defined as:

$$MSE(Y) = E((Y - f)^2) = \frac{1}{N} \sum_{i=1}^{N} r_i^2. \tag{7.4}$$

[1] Sometimes an error term, ϵ, is included in the regression - a random variable representing the error. This variable is assumed to be normally distributed with $E(\epsilon) = 0$ and $Var(\epsilon) = \sigma^2$ [59]. The quantity σ^2 is often called the error variance or residual variance. In this analysis we will look at errors and goodness of fit in other ways than merely identifying ϵ, so the term will not be used in this thesis.

The MSE provides a type of mean for the squared residuals [59].

Further, a second regression will be conducted, this time on the residuals from the model in Equation 7.1. This will help us because a *trend* in the residual approximations, implies that our original model is not good. For this regression we will use a simple linear model:

$$Y(X) = \lambda_1 + \lambda_2 X, \tag{7.5}$$

where λ_1 and λ_2 are constants, the regression parameters.

A hypothesis test will be conducted to see whether λ_2 is significant or not. The null hypothesis will be $H_0 : \lambda_2 = 0$, which is rejected if λ_2 is significantly different from zero. If this is the case, we have discovered a trend in the magnitude of the residuals, and a flaw in the original model. The t-tests are two-sided, with a 0.05 level of significance. This implies that a P-value lower than 0.025 must be found to reject H_0.

Finally, the certainty of the most important regression parameters and the plateau will be determined by a 95% confidence interval. This gives us a window of a certain size, in which we can be 95% certain we will find the subject parameter [51].

This report will not go into further details on regression, statistical tests, error measures or confidence intervals - the results and discussions will be the focus for the rest of the thesis. For more general information on statistics, consult [59, 54, 51, 36].

In the regression we will not include the initial distance of the attacker, because this value is considered to be collected outside the training program. The goal of the thesis is to identify learning, and for this the initial distance could be a misleading factor.

Some MATLAB example calculations are presented in Appendix B.6.

7.3 The Short-Term Hostile Scenario

This section will analyze the findings from the short-term hostile scenario. The design and results of this scenario was presented in Section 5.4.2 and 6.2, respectively.

7.3.1 Attacker A03

The regression analysis for Attacker A03 is shown in Table 7.1 and the curve is illustrated in Figure 7.2.

In the analysis only the initial distance was removed before the regression curve was calculated. The regression curve indicates that the participant is improving over the experiment time span, seen in Figure 7.2, as the dotted regression line is sloping downward.

Regression model	$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}$
Regression curve	$Y(X) = 12.5631 - 2.0455e^{\frac{-18.3582}{X}}$
Limit / Plateau	10.5176
β_1 **95% confidence interval**	$11.6061 < \beta_1 < 13.5201$
β_2 **95% confidence interval**	$-3.2307 < \beta_2 < -0.8603$
Plateau 95% confidence interval	$8.3753 <$ plateau < 12.6598
MSE	1.2573
Residual regression model	$Y(X) = \lambda_1 + \lambda_2 X$
Residual regression curve	$Y(X) = -0.0455 + 0.0013X$
λ_2 **confidence interval 95%**	$-0.0124 < \lambda_2 < 0.0150$
Residual MSE	1.2376
H$_0$	$\lambda_2 = 0$
H$_0$ P-value	0.8483 (Failed to reject H$_0$)

Table 7.1: Regression analysis for attacker A03. The regression curve converges to a plateau at 10.5176, and the curve is verified according to the regression of the residuals.

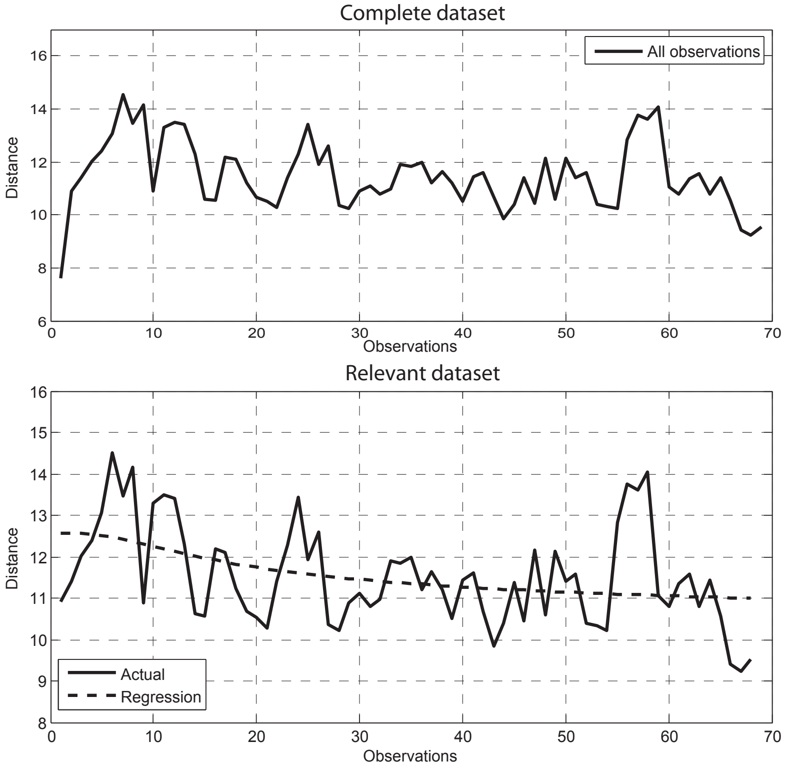


Figure 7.2: Attacker A03 learning curve. The top figure shows the entire collection of gait data for this attacker. In the bottom figure the initial distance has been removed because we only want data related to learning.

Looking at the full dataset on top of the figure, a point of resistance can be guessed around 11, much higher than the initial distance. The actual plateau is found when looking at the values to which the curve converges, in this case 10.5176.

The last three observations are the very lowest scores obtained for this attacker. In a case like this it would be interesting to continue the training to see if this means breaking through a plateau. If A03 in the future had managed to stay at that level, two plateaus could have been identified from the data. However, the data at hand is not enough to make such an assumption, and we will have to assume that the performance would have gone back up to the first plateau.

The fit of the curve is confirmed by the regression analysis in Table 7.1. The residuals have a mean of zero[2], and the slope of its regression line is not significant.

It is possible to identify a certain amount of improvement for this attacker, though the curve converges to 10.5176.

7.3.2 Attacker A04

The regression analysis for Attacker A04 is shown in Table 7.2 and the curve is illustrated in Figure 7.3.

Regression model	$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}$
Regression curve	$Y(X) = 11.3981 + 3.4070e^{\frac{-137.5858}{X}}$
Limit / Plateau	14.8051
β_1 **95% confidence interval**	$10.8866 < \beta_1 < 11.9095$
β_2 **95% confidence interval**	$-48.6264 < \beta_2 < 55,4482$
Plateau 95% confidence interval	$-37.6119 <$ plateau < 67.2221
MSE	1.6017
Residual regression model	$Y(X) = \lambda_1 + \lambda_2 X$
Residual regression curve	$Y(X) = 0.2055 - 0.0064X$
λ_2 **confidence interval 95%**	$-0.0237 < \lambda_2 < 0.0108$
Residual MSE	1.5613
$\mathbf{H_0}$	$\lambda_2 = 0$
$\mathbf{H_0}$ **P-value**	0.4610 (Failed to reject H_0)

Table 7.2: Regression analysis for attacker A04. The regression curve converges to a plateau at 14.8051, and the curve is verified according to the regression of the residuals.

The regression curve indicates worsening results, which can be seen in Figure 7.3, as the dotted regression line is sloping upwards. In the analysis the initial distance was excluded, in addition to some extreme outliers which were more than three standard deviations away from the overall mean. The plateau is found when looking at the values to which the curve converges, in this case 14.8051. However, very large confidence intervals were needed to support the regression curve, so drawing this conclusion might be a mistake. Actually the plateau's own confidence intervals spans from negative values with no meaning, to very high values. This can be seen

[2] The reader might have noticed that λ_1 is not zero, which one might expect if the overall residual mean is zero. However, in this regression λ_1 is not significantly different from zero, this can be proved by hypothesis testing identical to that for λ_2.

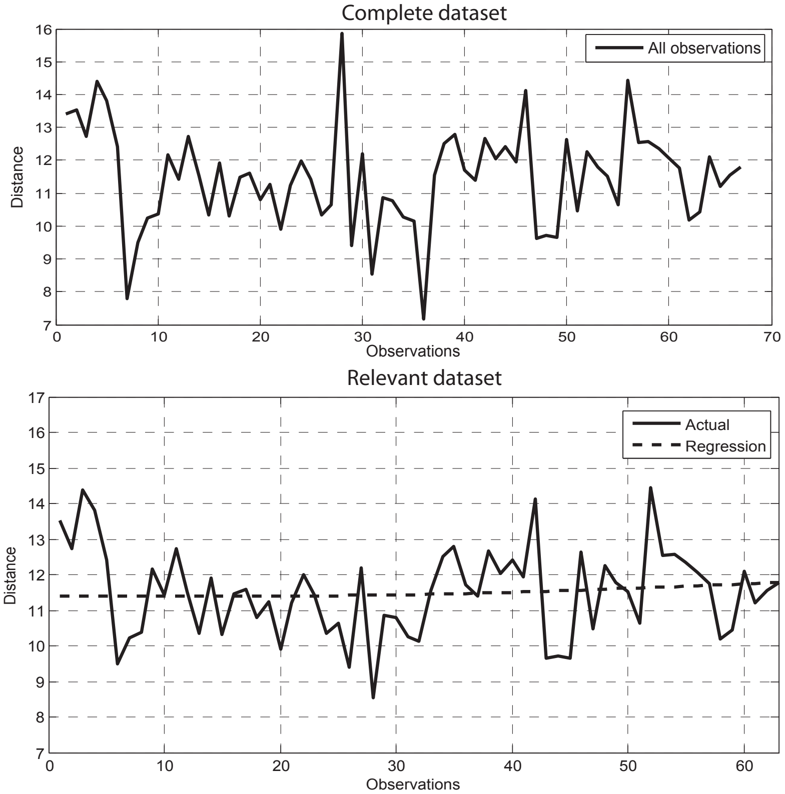


Figure 7.3: Attacker A04 learning curve. The top figure shows the entire collection of gait data for this attacker. In the bottom figure the initial distance has been removed because we only want data related to learning. Extreme outliers have been removed as well, which in this case involved three values more than three standard deviations away from the mean.

in Table 7.2, the regression analysis, which in fact is still defending the fit of the curve in terms of the residual regression. A slope equal to zero is a non-rejected hypothesis also in this case. The residuals have a mean of zero, and the slope of its regression line is not significant. Hence, the approximations seems to be valid from that point of view.

It is not easy to see exactly what is going on with A04, but at least it is easy to agree with the fact that the training is not doing much for him. Regression yields uncertain results, indicates a high plateau and no real improvement. However, given the uncertainties we cannot really say whether or not this attacker is learning.

7.3.3 Attacker A18

The regression analysis for Attacker A18 is shown in Table 7.3 and the curve is illustrated in Figure 7.4.

In the analysis the initial distance was removed before the regression curve was calculated, and some extrema were also removed, more than three standard deviations away from the mean. The regression curve indicates that the participant

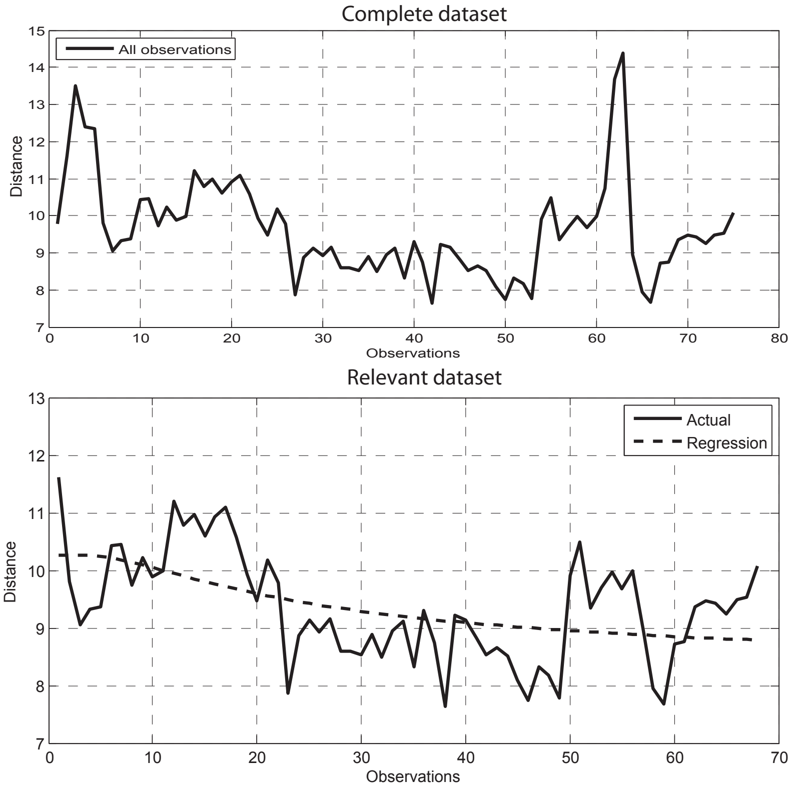


Figure 7.4: Attacker A18 learning curve. The top figure shows the entire collection of gait data for this attacker. In the bottom figure the initial distance has been removed because we only want data related to learning. Some extrema has also been removed, more than three standard deviations away from the mean.

Regression model	$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}$
Regression curve	$Y(X) = 10.2662 - 2.0549 e^{\frac{-22.3333}{X}}$
Limit / Plateau	8.2113
β_1 **95% confidence interval**	$9.6371 < \beta_1 < 10.8953$
β_2 **95% confidence interval**	$-3.0083 < \beta_2 < -1.1015$
Plateau 95% confidence interval	$6.6288 <$ plateau < 9.7939
MSE	0.6503
Residual regression model	$Y(X) = \lambda_1 + \lambda_2 X$
Residual regression curve	$Y(X) = -0.1179 + 0.0034X$
λ_2 **confidence interval 95%**	$-0.0064 < \lambda_2 < 0.0133$
Residual MSE	0.6358
H$_0$	$\lambda_2 = 0$
H$_0$ P-value	0.4901 (Failed to reject H$_0$)

Table 7.3: Regression analysis for attacker A18. The regression curve converges to a plateau at 8.2113, and the curve is verified according to the regression of the residuals.

is improving over the experiment time span, seen in Figure 7.4, as the dotted regression line is sloping downward.

The fluctuations in the observations could indicate that two plateaus exist (e.g. around 10 and 9), but it is also clear that after the attacker reaches the lower plateau, he is often forced back to the higher. Too little precise data is available in order to conclude with the existence of several plateaus, so it is more natural to use the result from the regression. The plateau is found when looking at the values to which the curve converges, in this case 8.2113.

The fit of the curve is confirmed by the regression analysis in Table 7.3. The residuals have a mean of zero, and the slope of its regression line is not significant.

It is possible to identify a certain amount of improvement for this attacker, but the results do seem to meet resistance from one or two plateaus. If we assume one plateau it is located somewhere in the interval $[6.6288, 9.7939]$ with 95% certainty.

7.3.4 Attacker A21

The regression analysis for Attacker A21 is shown in Table 7.4 and the curve is illustrated in Figure 7.5. The reader might recall this participant as the one having vast problems changing his gait characteristics. This is clearly visible in the figure, and will also become clear in the regression analysis.

The regression curve indicates worsening results, which can be seen easily in Figure 7.5, as the dotted regression line is sloping upwards. In the analysis the initial distance was excluded, in addition to two extreme outliers which were more than three standard deviations away from the overall mean. The plateau is found when looking at the values to which the curve converges, in this case 13.1676. The

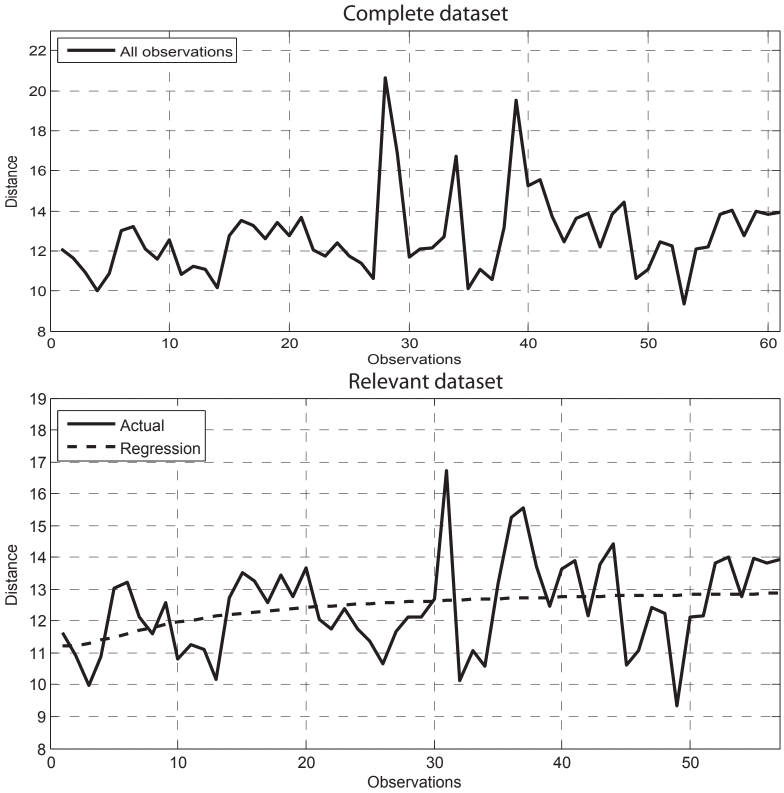


Figure 7.5: Attacker A21 learning curve. The top figure shows the entire collection of gait data for this attacker. In the bottom figure the initial distance has been removed because we only want data related to learning. Two extreme outliers have been removed as well, which in this case involved three values more than three standard deviations away from the mean.

Regression model	$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}$
Regression curve	$Y(X) = 11.2132 + 1.9545e^{\frac{-9.5868}{X}}$
Limit / Plateau	13.1676
β_1 **95% confidence interval**	$9.5339 < \beta_1 < 12.8924$
β_2 **95% confidence interval**	$0.3335 < \beta_2 < 3.5755$
Plateau 95% confidence interval	$9.8674 <$ plateau < 16.4679
MSE	1.9803
Residual regression model	$Y(X) = \lambda_1 + \lambda_2 X$
Residual regression curve	$Y(X) = -0.0603 + 0.0021X$
λ_2 **confidence interval 95%**	$-0.0237 < \lambda_2 < 0.0108$
Residual MSE	1.9431
$\mathbf{H}_0$	$\lambda_2 = 0$
$\mathbf{H}_0$ **P-value**	0.8536 (Failed to reject H_0)

Table 7.4: Regression analysis for attacker A21. The regression curve converges to a plateau at 13.1676, and the curve is verified according to the regression of the residuals.

residuals have a mean of zero, and the slope of its regression line is not significant. Hence, the approximations are valid from this point of view.

The training effort did not seem to do much for A21, and as Figure 7.5 clearly shows - the results are worsening over time. Due to the test subjects lack of mimicing and gait adoption skills, his natural fluctuations are somewhat high. It is still reasonable to assume a plateau within the confidence interval in Table 7.4. Conclusions are left for the last part of this section.

7.3.5 Attacker A38

The regression analysis for Attacker A38 is shown in Table 7.5 and the curve is illustrated in Figure 7.6. As described in the previous chapter, this attacker made a vast initial improvement, but then saw her results slowly increase and stabilize.

The regression curve indicates worsening results, which can be seen easily in Figure 7.6, as the dotted regression line is sloping upwards. In the analysis some extreme outliers were removed because they had nothing to do with the learning process. In this case it involved four values more than four standard deviations away from the mean.

Looking at the full dataset (top of Figure 7.6), it is very easy to spot a point of resistance for this attacker. Intuitively, one might assume a plateau around 11. The actual plateau is found when looking at the values to which the curve converges, in this case 13.3554.

Why is this attacker performing so poorly? The reader should really note the exceptionally high initial distance of this attacker, compared to her results during the mimicking. As we remove the initial distance before the regression, A38 starts

Regression model	$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}$
Regression curve	$Y(X) = 8.5539 + 4.8016e^{\frac{-28.5555}{X}}$
Limit / Plateau	13.3554
β_1 **95% confidence interval**	$7.8693 < \beta_1 < 9.2384$
β_2 **95% confidence interval**	$3.0515 < \beta_2 < 6.5517$
Plateau 95% confidence interval	$10.9208 <$ plateau < 15.7901
MSE	0.9236
Residual regression model	$Y(X) = \lambda_1 + \lambda_2 X$
Residual regression curve	$Y(X) = 0.0375 - 0.0012X$
λ_2 **confidence interval 95%**	$-0.0154 < \lambda_2 < 0.0130$
Residual MSE	0.9072
H$_0$	$\lambda_2 = 0$
H$_0$ P-value	0.8630 (Failed to reject H$_0$)

Table 7.5: Regression analysis for attacker A38. The regression curve converges to a plateau at 13.3554, and the curve is verified according to the regression of the residuals.

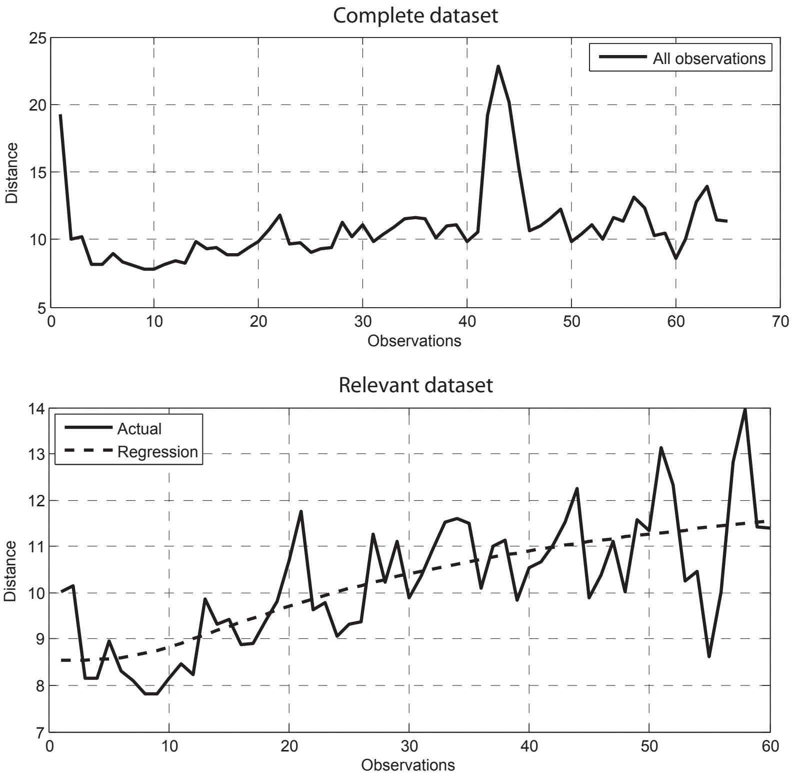


Figure 7.6: Attacker A38 learning curve. The top figure shows the entire collection of gait data for this attacker. In the bottom figure the initial distance has been removed because we only want data related to learning. Extreme outliers have been removed as well, which in this case involved four values more than four standard deviations away from the mean.

out her mimicing below her natural plateau. Her performance slowly worsens, and the approximation converges to the plateau.

The fit of the curve is confirmed by the regression analysis in Table 7.5. The residuals have a mean of zero, and the slope of its regression line is not significant.

The summary will include final conclusions on the short-term hostile scenario, but it is clear that without the initial distance included A38's performance is almost constantly worsening, indicating that the training did absolutely nothing to help her mimic.

7.3.6 Attacker A41

The regression analysis for Attacker A41 is shown in Table 7.6 and the curve is illustrated in Figure 7.7. The reader might recall that this attacker experienced an increase in performance during his last attempts to mimic. This clearly affects the results in this section.

Regression model	$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}$
Regression curve	$Y(X) = 11.9737 - 697.5238e^{\frac{-363.1937}{X}}$
Limit / Plateau	-685.5501
β_1 **95% confidence interval**	$11.5833 < \beta_1 < 12.3640$
β_2 **95% confidence interval**	$-4914.8475 < \beta_2 < 3518.8208$
Plateau 95% confidence interval	$-4903.2642 < \text{ plateau } < 3531.1849$
MSE	1.4963
Residual regression model	$Y(X) = \lambda_1 + \lambda_2 X$
Residual regression curve	$Y(X) = 0.0885 - 0.0027X$
λ_2 **confidence interval 95%**	$-0.0187 < \lambda_2 < 0.0133$
Residual MSE	1.4700
H$_0$	$\lambda_2 = 0$
H$_0$ P-value	0.7391 (Failed to reject H$_0$)

Table 7.6: Regression analysis for attacker A41. The regression curve converges to -685.5501, and the curve is verified according to the regression of the residuals.

As before, the initial distance and four extrema were removed from the result data, the latter more than three standard deviations away from the mean. The regression curve indicates that the participant is improving over the experiment time span, seen in Figure 7.7, as the dotted regression line is sloping downward.

It is very interesting to analyze this attacker visually. The regression curve lies very firmly around the distance value 12, but then plunges down in the end. The improvement seen at this point is large enough to affect the results dramatically - the estimated point of convergence is -685.5501, which is meaningless. Hence, something has happened here that the model cannot explain - could this be the presence of a second plateau?

A plateau at 12 that is broken could indeed explain some of this behavior. For a long time the attacker is stuck at this point, and then suddenly decreases his distance with

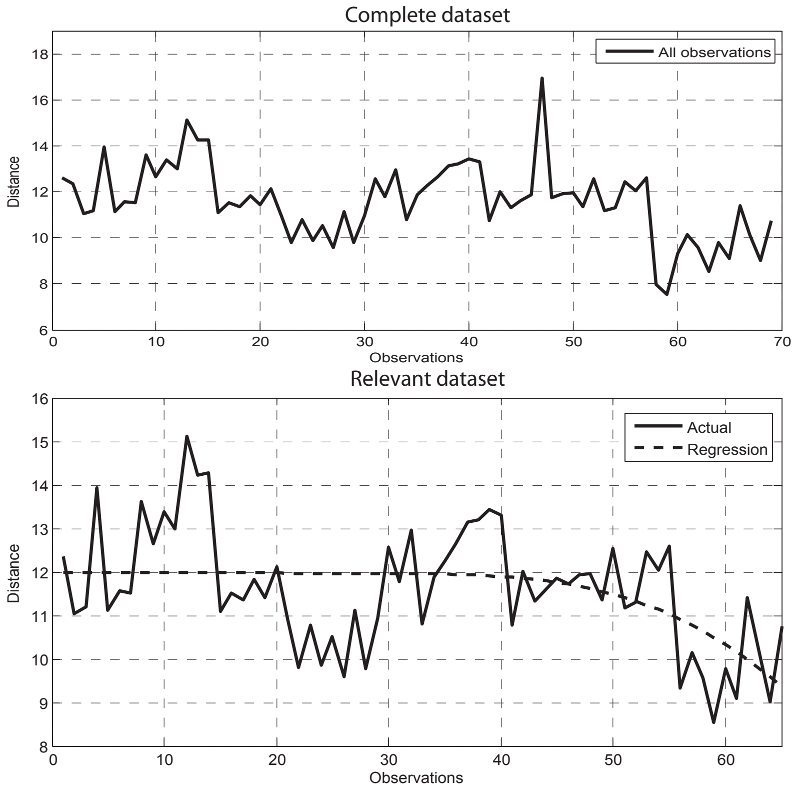


Figure 7.7: Attacker A41 learning curve. The top figure shows the entire collection of gait data for this attacker. In the bottom figure the initial distance has been removed because we only want data related to learning.

2 points, and seems to stabilize there. Unfortunately, there is not enough data to be sure - for all we know he is just about to return to the initial plateau.

The fit of the curve is confirmed by the regression analysis in Table 7.6. The residuals have a mean of zero, and the slope of its regression line is not significant. The approximations are valid from this point of view, but it is already clear that the strange behavior of the regression model must be due to something it cannot describe - at least not with this limited amount of data.

In general we cannot say anything about this attacker without more data. It is reasonable to assume that further training would result in either returning to the higher plateau around 12, or continuing at a new, lower level around 10. It is tempting to see this as an indicator of learning.

7.3.7 Conclusions on the Short-Term Scenario

The most precise and clearly defined regression curves are the ones for attacker A03, A18, A21 and A38. These have well-defined limits with practical interpretations, and a single plateau is identified for each of them. All the regression curves are verified by residual regression, and the certainty of the regression parameters are acceptable. The plateaus are identified with 95% certainty using confidence intervals: $[8.3753, 12.6598]$, $[6.6288, 9.7939]$, $[9.8674, 16.4679]$ and $[10.9208, 15.7901]$, respectively.

At this point it is interesting to look at the threshold obtained in Section 6.1: 8.6449, for an EER of 6.2%. Two of the confidence intervals above contains this value, and the plateau of A18 is actually below this threshold and would be a threat to the software developed for this thesis. However, implementing a real system would involve optimizing several components of the technology, and hopefully result in a much lower threshold.

Regression for A04 was more problematic. The regression of A04 did result in a curve with an acceptable fit and a clearly defined limit, but the regression parameters are very uncertain. The reason for this is not clear, and with more time perhaps a more customized regression model could be the key to success. The estimated plateau is not the problem (14.8051), but the corresponding 95% confidence interval is large: $[-37.6119, 67.2221]$. This interval spans values with no practical interpretation.

A41's results also troubled the regression, but in an entirely different way. The limit for A41 is -685.5501, which has no interpretation, and the corresponding 95% confidence interval is huge: $[-4903.2642, 3531.1849]$. Despite the fact that the fit of the curve is validated by residual regression, the regression analysis alone does not provide much information. The interesting part of this result is bound to involve some speculations - as mentioned earlier one possible explaination could be the breaking through a plateau, and landing on another.

Four out of six attackers are unproblematic in terms of regression analysis - A03, A18, A21 and A38. The former two have downward-sloping regression curves, which indicate improving performance, and the latter two have upward-sloping curves, indicating worsening performance. As the reader surely have picked up in this section - very little learning has been observed. Even if some curves slope downwards, they converge quickly to higher thresholds. In the case of upward-sloping curves, learning is obviously not present here either.

Due to the uncertain results of A04 and A41, one should be critical to using it directly. For completeness it should be mentioned the former attacker also has an upward-sloping curve with no learning present, and the latter attacker is very stable until the last few attempts.

7.4 The Long-Term Hostile Scenario

The regression analysis for Attacker A01 is shown in Table 7.7 and the curve is illustrated in Figure 7.8. This is the long-term results, for attacker A01. The design and results from this scenario are found in Section 5.4.3 and 6.3.

The regression curve indicates worsening results, which can be seen in Figure 7.8, as the dotted regression line is sloping upwards. In the analysis some extreme outliers were removed, in this case 3.5 standard deviations away from the mean.

Regression model	$Y(X) = \beta_1 + \beta_2 e^{\frac{\beta_3}{X}}$
Regression curve	$Y(X) = 13.9962 + 0.2588e^{\frac{-19.8894}{X}}$
Limit / Plateau	14.2550
β_1 **95% confidence interval**	$12.7169 < \beta_1 < 15.2755$
β_2 **95% confidence interval**	$-0.9570 < \beta_2 < 1.4746$
Plateau 95% confidence interval	$11.7599 <$ plateau < 16.7501
MSE	2.7667
Residual regression model	$Y(X) = \lambda_1 + \lambda_2 X$
Residual regression curve	$Y(X) = 0.2036 - 0.0026X$
λ_2 **confidence interval 95%**	$-0.0086 < \lambda_2 < 0.0033$
Residual MSE	2.7347
$\mathbf{H_0}$	$\lambda_2 = 0$
$\mathbf{H_0}$ **P-value**	0.3819 (Failed to reject H_0)

Table 7.7: Regression analysis for the long-term attacker A01. The regression curve converges to 14.2550, and the curve is verified according to the regression of the residuals.

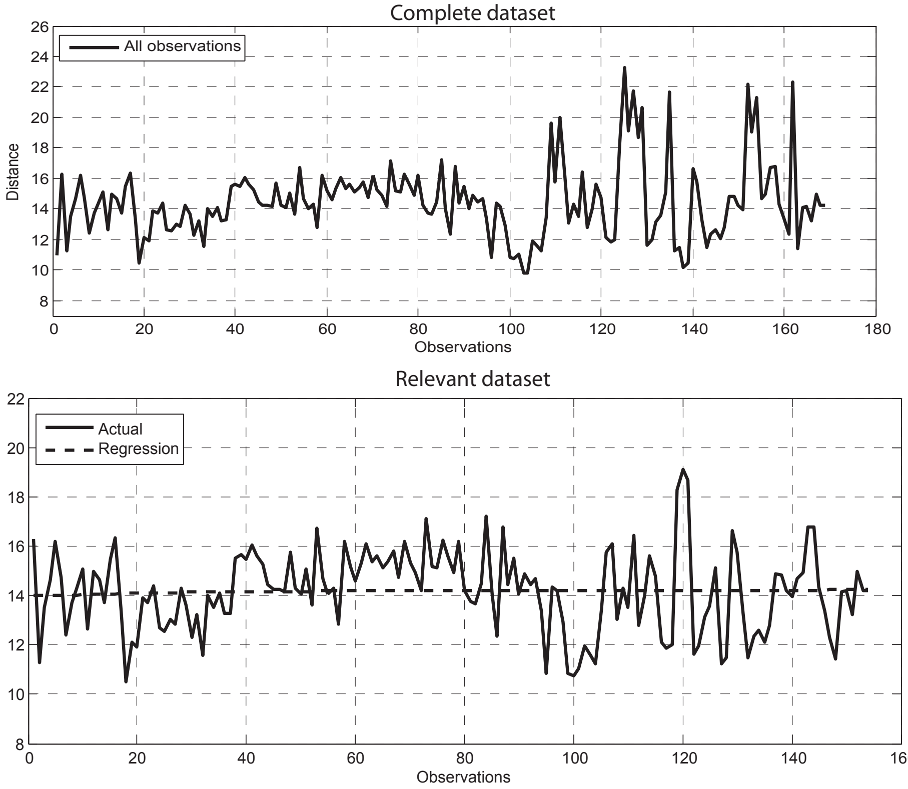


Figure 7.8: Long-term attacker A01 learning curve. The top figure shows the entire collection of gait data for this attacker. In the bottom figure the initial distance has been removed because we only want data related to learning. Extreme outliers have been removed as well, which in this case involved values more than 3.5 standard deviations away from the mean.

Looking at the full dataset, resistance can be identified around 14 and 12. There is something particularly interesting with this scenario, but before we get to this - the regression indicates a plateau, found when looking at the values to which the curve converges, in this case 14.2550.

The fit of the curve is confirmed by the regression analysis. The residuals have a mean of zero, and the slope of its regression line is not significant.

The reader is encouraged to study Figure 7.8 closely, and notice that approximately after $80 - 90$ WALKS something happens. Until then the results were quite stable around the plateau identified through regression. After that however, variance increases dramatically.

The reader might recall from Chapter 6 that A01 discovered a way to increase performance. This first brought a series of good results, but then it became difficult to reproduce them the following days. A01 was certain this could be the key to better results, and kept training, but it was very hard. The figure shows failed and successful attempts of adopting this specific gait characteristic, and hence the results oscillate to a very high degree in this period.

So is this interesting, and relevant? Indeed it is, because it gives a strong indication that two plateaus exist for this participant. A01 strongly felt that with a lot more training, he should be able to stabilize the gait characteristic, and thus achieve better results that what the first half of the plot shows us.

Even with the long-term scenario we need more data to make accurate estimates and proofs. However, it is reasonable to assume that indeed this bettering of performance is possible - a claim based on a lot of experience and analysis.

To analyze two plateaus it would be necessary to split the graph in two, say, on 80 WALKS, and perform a regression analysis on both. Without more stable data this cannot be done properly.

So is A01 learning? We can hardly say he is improving much, even if a new plateau is found. Reaching the second plateau requires very high effort, and we do not even know it would ever happen in a stable manner. Also, if A01 did reach the second plateau in the future, it would still lie significantly higher than the threshold of acceptance: 8.6449. If a successful attack on the biometric software was to be conducted, a third or fourth plateau would have to exist - and these would most likely be even harder to reach, maybe impossible.

At this point it is interesting to look back on A41's results. His curve ”breaks” in the very end, making the regression plunge downwards to a negative plateau with no meaning. This can be compared to the results of A01 where the first improvement is identified - if A01 stabilized at, say, 11 - his curve would also plunge. In other words, when the regression curve converges to a meaningless plateau, it could mean that another plateau is broken. In the case of A41 the first plateau lies around 12.

Final remarks on these observations will be made in the conclusions, Chapter 9.

7.5 The Research Questions

It is time to look back and see if we can answer the research questions from the introductory parts of the thesis. These questions were the guidelines when designing the experiment, and sums up the main motivation behind the entire thesis.

Will extensive training of individuals affect their ability to mimic gait?
Indeed, it is possible to affect the performance of gait mimicking using training and feedback. By experimenting with small and large changes of gait characteristics, not spending time on bad ideas, and concentrate on the clues that improve performance, a few attackers did move somewhat closer to the victim.

However, the increase in performance is very limited. It is clear from the analysis in this chapter, that the attackers met their natural boundaries and had huge problems moving on from that point. These plateaus were found for six out of seven attackers, and indicate that even if you can train to adopt certain characteristics of your victim, the outcome of your attempt is predetermined by your plateau. If it lies too high, you will never be able to mimic that person. And most attackers actually experienced **worsening** performance, converging towards a plateau far above the acceptance threshold. As they trained, they often felt that their walk became unnatural and mechanical.

What can contradict the assumption of a predetermined outcome, is the existence of *several* plateaus. The long-term scenario did provide one such indication, but not enough data is available to make a claim. However, the observations also indicated that the assumed new plateau was extremely hard to reach - and the performance had high fluctuation. One possibility could be that the *real* plateau is the lower plateau, and that the higher results are just a effect of bad mimicking. Either way - if the reader chooses to believe in the single plateau, or the many, learning seems inadequate to pose a threat. Even with many plateaus, reaching the second requires extreme effort, and then we can only imagine what the third would be like.

Extensive training is a relative term, but at the time of writing the training conducted during this thesis is definitely qualified. Only minimal-effort experiments have been conducted previously. Two and six weeks are not huge time spans, so it is important to stress that the results are indicators, and not definite conclusions. However, one can feel confident that if someone extends the training to a three or four year long program, the general indicators on non-significant learning will persist. Before the experiment was over, several attackers already felt that they had done all they could to mimic the victim, and whatever they did they either worsened results or stayed put. They could not concentrate on several characteristics at the same time, and they kept forgetting details about previous achievements. If they were reminded of those details, it was still too difficult to think of them all simultaneously. Mimicking gait is difficult, and our physiology is working against us.

Is mimicking easier for an individual who's normal gait is similar to the victim?
In the conclusions of this thesis, suggestions will be made for future work, and this question is applicable because the number of participants could not be very

high in this research. The initial distances for the attackers in this experiment were $11.04, 7.62, 13.4, 9.79, 12.1, 19.3$ and 12.6. A better suited group for investigating this topic would be one where, say, ten participants started out with initial distance around 8, and ten more started out at 20. Such an experiment however, would take much more time than what was available for this research..

Some observations can still be made. We have seen A38 starting out very high, and immediately plunge down when attempting to mimic. Still, she hit the same kind of resistance, far above the threshold needed to break the software tool. On the other hand, we have seen A01 and A03 starting out much closer to the threshold, but then actually worsen performance significantly until the plateau is reached. Other attackers start out somewhere in between of these extremes, and stay there.

From this it is reasonable to assume that someone walking very similar to a victim, will in general be prone to worsening performance when attempting to mimic. This makes sense because adopting gait characteristics often causes a chain of changes in the body movement, also changing characteristics that originally were similar to those of the victim. The logic is reversible - if your gait is extremely different from the victim, doing some changes can hardly ever make you *increase* the distance, and it will probably cause a chain of changes that moves you in the right direction.

This can be summed up neatly as having a natural plateau some distance from the victim. If you start out below it, your mimicking pulls you back up, and vica versa.

What kind of feedback and available sources of information affects the performance of an impostor's mimicking?

All changes of gait characteristics affect the results, so the training concentrated on finding the right sort of changes. What is important is what sources of information provides the *best* feedback.

The attackers all spent a high amount of time watching videos. Some preferred videos of their own gait, or the victim's gait alone, but overall the most valuable video clips were those where both the victim and the attacker walked together. This really provides an opportunity to study minor differences in great detail, as well as looking at the high-level characteristics like posture. The frontal video clips turned out to be especially well-suited for this, but also the back and sideways clips were extensively studied.

Walking next to and watching the victim in a live session did not seem to provide a lot of information, except from the video tape of the two in action. It is difficult for the attacker to concentrate on walking naturally and picking up information from live gait simultaneously. It did however affect speed and posture in an improving manner, for most attackers.

Despite good use of the video clips, the most important feedback factor was the statistical results themselves. These track improvement! Some characteristics seemed easy to adopt physically, but gave horrible results in the experiment. Such feedback is crucial, and makes the training much more time efficient. During the long-term experiment, A01 actually did not use the video clips much, except in the very beginning. This is due to another discovery - sometimes it is not necessary, or even smart, to try to mimic the victim, but rather find ”shortcuts” by trial and error. The participants were allowed to follow this strategy if they wanted, examples from Chapter 6 are alternating tapping of pockets, and holding the upper body still. These shortcuts are characteristics that the victim does not necessarily exhibit himself, but still has a positive effect on the results. The statistical feedback is the only medium of feedback that can help an attacker with this approach, and the attackers found it very valuable.

Chapter 8

Future Work

There are many exciting possibilities for **future work** on gait biometrics. For gait mimicking in particular - this thesis cannot provide definite answers because the data set is not large enough. In order to safely commercialize gait biometrics, an even more extensive experiment should be conducted. This would typically have to include paying participants to train over one or more years.

Different results might be achieved if the gait analysis scheme is significantly changed. For instance, if FFT was used in order to look on gait in the frequency domain, we might see other trends and characteristics in the attackers performance. Of course, a lot of the observations in the thesis are generalizable - like the fact that physiological boundaries makes gait mimicking difficult, but we cannot claim to be 100% sure that our observations hold under all circumstances. A future task could be to perform the same experiment with different analysis tools.

Other aspects of mimicking could also be analyzed - like threats through cooperation. Cooperation in gait mimicking essentially means that two people try to walk like each other, and then maybe ”meet in the middle”. Hence, one person could enroll walking somewhat like a different person and, if successful, they could both authenticate with the same template.

Proper experiments on gender differences have not been conducted either, as well as differences between high and low distance attackers - are people with similar gaits more threatening than those who walk very different? This thesis cannot make conclusions on this directly, though the results do not show any clear differences.

It would also be interesting to get precise physiological explanations on *why* it is so hard to imitate other people’s walks. For this, medical studies would come into play, and a successful report on the topic would definitely strengthen the documented security of gait biometrics.

On the field of gait biometrics in general there is a lot of work to do. The performance of gait recognition systems are not generally competitive to other biometrics at the time of writing, so the invention of new methods, and further development of the existing methods is necessary. At the current state of the art, gait biometrics is merely secure enough for use in ”fun applications”, where the curiosity of recognizing someone on their walk is the main value. For such applications the high error rates are not problematic.

Chapter 9

Conclusions

We tested the security strength of gait biometrics against imitation. A software tool for gait recognition was successfully designed and implemented (Chapter 4), and the choices of methods were rooted in the current technological state of the art (Chapter 3). The software was based on analyzing acceleration during walk, relative to the users hip in three dimensions.

An experiment consisting of three scenarios was conducted, where the ultimate goal was to train participants to be able to mimic the gait of a preselected victim. Chapter 5 presented the design of this experiment, while Chapter 6 presented the results. The research intended to determine whether or not the mimicking skills of the participants improved over time. This is interesting because if it turns out to be easy to learn how to walk like someone else, then the potential of gait biometrics as an authentication mechanism decreases dramatically.

The first scenario was a ”friendly” scenario, where 50 participants were enrolled into the biometric system. The results from this particular scenario were presented in Section 6.1, which confirmed that the developed software performed well - with an EER of 6.2% it can be categorized among the best performances seen in the field so far.

The second scenario of the experiment was a hostile scenario, where six participants trained extensively with the common goal in mind - to mimic the gait of the victim. The training period lasted for two weeks, and consisted of five sessions, lasting an hour each.

The third scenario was also a hostile scenario, but this time only one attacker participated. This scenario differed from the second by an extended training period that lasted for six weeks, and was a lot more intensive. Hence, this part of the experiment constituted a long-term hostile scenario. Also, after conducting the second part of the experiment, experience and expertise was gained on the particular gait of the victim, giving the scenario a better starting point.

In Section 1.3 three research questions were raised, and in Section 7.5 they were answered. Put in short, the participants did not show a significant improvement, learning over time was not present. A regression analysis was conducted in Chapter 7 to establish this fact - most learning curves were sloping upwards (A01, A04, A21 and A38), indicating worsening performance. This agrees with the observations made by Gafurov in [26, 25] (see Section 3.4.1) - the attackers seem to be better off if they do not train for anything. Among the stable regression results, A18 constituted the only attacker with a downward sloping curve.

Here we can mention that even if a learning curve is sloping upwards, it does not have to mean the attacker cannot learn anything at all. Looking for instance at the attacker A38, she increases her performance significantly from the initial result collected at the friendly scenario, to the first mimicking attempt. However, this improvement is not included in the regression, because it is not a part of the training process. So easily put: A38 is not entirely incapable of changing the way she walks, but training will not improve her skills in mimicking another person.

It seemed like everyone hit a natural boundary that prevented them from improving their performance beyond a certain point. This observation was so striking that the phenomenon was given a name: a *plateau*. The plateau was introduced in the beginning of Chapter 7, and the following remarks summarizes the findings of this chapter.

The plateau is an individuals limit to learning how to mimic gait, it is different for everyone and thus physiologically predetermined. If only one such plateau exists, then it is mathematically the same as a *limit*, in essence - the value to which the learning curve converges. Natural fluctuations will be present, depending on the participants gait stability (i.e. variance), but the plateau will act like a magnet, and pull the results towards it in one direction or the other.

A single plateau was identified for almost every participant. However, some data suggest that in some cases an individual can exhibit two or more plateaus. This is why the term ”plateau” was chosen - it is not as strict as the mathematical definition of a limit. For the long-term attacker A01, results and experiences indicated that with more time the plateau could be broken, and a new plateau could be found at a level of higher performance. Slight indications for this were also observed for one short-term attacker (A41).

To succeed in a mimicking attack with a single plateau, the plateau itself must lie below or close to the threshold of acceptance. That is, natural fluctuations may cause some successful attempts even if the plateau is above the threshold. This depends on the variance of the gait. However, only one attacker posed a threat to the victim.

In order to succeed in a mimicking attack with several plateaus, the attacker has to reach a plateau that has the same properties as the one described above - close to or below the threshold. The data that suggested a second plateau in the experiment, also indicated that the plateau was very hard to reach. And even the second plateau would not constitute a threat - so in essence it seems almost as hard to break through one plateau, as it is to beat the system in general. It is also likely that plateaus get harder to break the closer to the threshold they are.

It should be noted that the findings of this thesis cannot necessarily be generalized to apply to other analysis methods. The results here applies to the combination of methods and configurations presented in this report, and one cannot be sure that the results would look the same, say, in the frequency domain. However, a lot of the difficulties in gait mimicking are likely to be physiologically rooted, and thus it is reasonable to assume that the indicators are relevant in other contexts as well.

Summarized, the attackers had varying skills and results, and only one of them got to a plateau below the threshold. If we consider a future improvement in gait biometrics, that one attacker is nothing to worry about. What is much more important - the attackers hardly learned at all. Their improvements are insignificant and they struggle hard to adopt even one single gait characteristic. If one such characteristic improves, we see other characteristics worsen in a chain-like effect. As said before, our physiology makes the task extremely difficult, if not impossible.

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Appendix A

Collected Data

A.1 The Friendly Scenario

During the friendly scenario 50 participants submitted gait data, ten templates were created for each one. To create the DET curve in Figure A.1 comparisons were made among all 500 templates. Alltogether this constitutes 124750 comparisons, whereof 2250 are genuine and 122500 are impostor trials, for which an EER of 6.2% was achieved. Instead of reproducing every single comparisons, Table A.1 and A.2 show the **average** DTW distance between every pair of participants. A DET curve for this matrix is shown in Figure A.1 (to the right), where the EER is as low as 1.92.

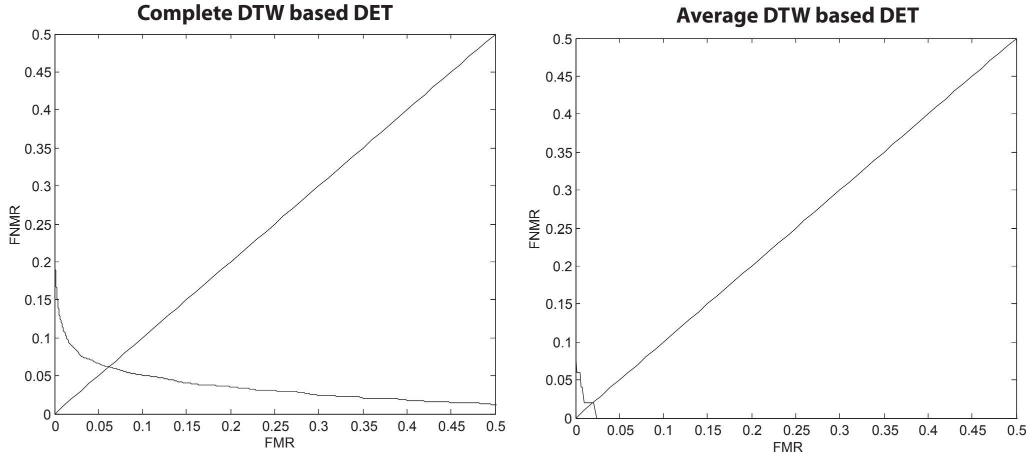


Figure A.1: Left: DET curve from the friendly scenario, EER = 6.2%. Right: DET curve based on average DTW distances, EER = 1.92%.

Table A.3 and A.4 show the standard deviation corresponding to the average DTW distances between every pair of participants.

	TS01	TS02	TS03*	TS04*	TS05	TS06	TS07	TS08	TS09	TS10	TS11	TS12	TS13	TS14	TS15	TS16	TS17	TS18*	TS19
TS01	3,366	11,29	10,43	15,11	11,39	11,8	16,34	15,05	12,32	11,63	12	13,48	13,25	13,96	16,16	11,04	13,09	12,65	16,78
TS02	11,29	3,199	8,391	12,04	10,34	10,41	14,79	10,01	13,19	11,63	10,32	9,89	10,29	12,1	11,8	9,601	9,255	6,727	13,02
TS03*	10,43	8,391	2,965	11,26	12,58	8,718	14,12	12,39	14,13	8,044	11,75	11,68	9,97	12,28	13,64	7,618	10,11	9,996	14,4
TS04*	15,11	12,04	11,26	7,548	12,34	10,34	12,99	14,79	20,09	15,95	16,02	13,02	9,099	10,65	12,13	13,37	12,29	11,47	15,02
TS05	11,39	10,34	12,58	12,34	3,927	10,91	14,8	13,59	14,77	14,55	13,28	11,14	12,62	14,4	11,68	12,32	15,28	11,31	16,32
TS06	11,8	10,41	8,718	10,34	10,91	5,141	10,79	14,78	16,96	12,79	14,76	13,69	8,262	10,52	14,96	11,24	10,59	11,79	17,43
TS07	16,34	14,79	14,12	12,99	14,8	10,79	6,122	16,68	21,27	18,8	17,82	17,69	11,69	13,17	16,44	16,71	15,75	14,93	21,42
TS08	15,05	10,01	12,39	14,79	13,59	14,78	16,68	5,747	13,76	12,71	10,79	10,64	14,87	14,11	10,49	10,86	10,49	9,446	11,11
TS09	12,32	13,19	14,13	20,09	14,77	16,96	21,27	13,76	3,414	11,75	8,806	12,38	19,11	18,13	15,83	12,61	14,86	13,8	14,51
TS10	11,63	11,63	8,044	15,95	14,55	12,79	18,8	12,71	11,75	3,648	10,34	11,97	14,48	16,09	13,85	8,985	10,25	11,26	13,41
TS11	12	10,32	11,75	16,02	13,28	14,76	17,82	10,79	8,806	10,34	3,381	10,43	15,02	14,58	12,72	10,03	11,63	10,89	11,62
TS12	13,48	9,89	11,68	13,02	11,14	13,69	17,69	10,64	12,38	11,97	10,43	3,314	13,02	12,71	8,018	10,42	8,855	9,273	12,12
TS13	13,25	10,29	9,97	9,099	12,62	8,262	11,69	14,87	19,11	14,48	15,02	13,02	4,153	9,677	12,51	11,65	10,7	10,21	15,77
TS14	13,96	12,1	12,28	10,65	14,4	10,52	13,17	14,11	18,13	16,09	14,58	12,71	9,677	7,062	12,59	13,5	11,1	10,72	14,7
TS15	16,16	11,8	13,64	12,13	11,68	14,96	16,44	10,49	15,83	13,85	12,72	8,018	12,51	12,59	6,173	11,16	9,302	10,29	12,49
TS16	11,04	9,601	7,618	13,37	12,32	11,24	16,71	10,86	12,61	8,985	10,03	10,42	11,65	13,5	11,16	4,373	9,416	9,787	10,79
TS17	13,09	9,255	10,11	12,29	15,28	10,59	15,75	10,49	14,86	10,25	11,63	8,855	10,7	11,1	9,302	9,416	3,985	9,012	10,52
TS18*	12,65	6,727	9,996	11,47	11,31	11,79	14,93	9,446	13,8	11,26	10,89	9,273	10,21	10,72	10,29	9,787	9,012	2,891	10,41
TS19	16,78	13,02	14,4	15,02	16,32	17,43	21,42	11,11	14,51	13,41	11,62	12,12	15,77	14,7	12,49	10,79	10,52	10,41	5,581
TS20	12,7	15,65	11,03	19,24	15,98	15,59	20,92	14,38	12,56	10,49	10,76	12,28	18,85	19,82	12,69	12,08	14,42	14,37	12,27
TS21*	12,74	10,12	12,89	14,17	11,42	13,65	18,96	14,13	13,09	12,97	13,22	8,714	13,31	14,48	11,45	12,15	10,02	9,5	14,23
TS22	15,19	10,44	12,8	14,35	14,39	14,97	18,23	11,8	13,79	11,71	10,28	7,367	12,28	13,44	9,742	10,98	8,152	9,89	11,87
TS23	12,19	10,2	12,13	14,46	14,41	14,38	16,51	8,312	13,19	11,75	9,199	9,59	13,74	12,69	9,896	10,54	9,057	9,53	11,13
TS24	13,18	10,66	11,34	16,85	13,44	15,34	19,43	10,77	9,705	8,988	7,681	10,92	16,04	16,89	12,32	9,448	12,38	10,89	11,5
TS25	12,37	11,65	11,43	14,33	12,09	10,46	14,59	14,47	14,87	12,89	13,08	11,41	12,28	15,26	13,63	12,87	13,48	10,27	16,13
TS26	10,29	12,72	13,06	19,13	13,69	15,93	19,47	15,5	7,417	13,12	11,12	13,1	18,41	17,46	16,32	13,42	15,26	15,11	16,94
TS27	10,96	12,22	12,13	16,46	11,93	13,32	16,82	14,18	10,71	12,42	10,77	11,27	15,55	14,51	13,07	12,78	11,9	11,34	15,3
TS28	11,65	12,8	7,817	12,96	15,6	10,59	14,04	14,37	16,08	11,47	13,6	13,02	12,47	11,03	13,53	11,8	9,397	12,64	15,47
TS29	17,69	10,35	15,11	12,79	16,96	11,15	15,19	10,62	16,29	13,56	15,08	8,506	12,1	11,11	8,562	13,04	7,266	10,4	11,52
TS30	8,341	11,26	10,95	16,84	11,94	13,22	18,72	13,27	8,72	9,972	10,08	10,2	15,63	16,43	12,46	10,29	10,84	12,08	14,14
TS31	13,59	11,38	9,763	14,44	13,92	12,67	19,03	13,83	13,96	10,04	10,65	12,07	12,81	14,77	12,67	9,353	10,67	10,77	10,39
TS32	15,3	8,758	11,39	12,03	13,83	13,97	17,65	11,74	15,78	11,35	11,71	8,611	10,77	12,93	9,807	10,61	7,496	8,297	12,37
TS33	13,69	10,32	10,66	11,56	13,98	9,643	14,55	13,41	16,94	10,98	14,55	10,81	9,741	11,77	11,86	12,5	9,319	9,976	15,25
TS34	12,58	13,05	14,7	16,05	13,01	14,43	17,78	12,83	16,09	15,59	13,46	11,24	16,7	15,57	11,8	15,24	13,88	12,26	14,93
TS35	11,24	10,53	10,56	13,08	9,779	10,12	13,74	12,49	14,8	11,72	12	10,74	10,82	12,92	11,21	11,05	13,04	9,011	16,52
TS36	20,56	13,36	16,57	13,59	18,22	15,5	15,82	13,12	23,13	18,18	16,09	13,81	12,74	12,83	12,68	16,48	12,82	11,96	14,8
TS37	14,6	11,5	10,9	17,06	16,24	14,49	18,7	11,57	12,98	9,689	10,23	11,6	16,2	16,62	12,74	10,79	12,22	12,24	13,31
TS38*	21,8	17,44	19,65	14,7	20,4	17,67	19,42	18,34	24,12	23,17	19,92	16,4	14	15,24	15,24	19,33	15,86	15,37	18,36
TS39	10,26	9,311	8,713	13,32	11,58	11,94	16,33	9,656	12,93	10,25	9,687	10,28	11,88	12,17	10,46	8,68	7,892	8,989	10,17
TS40	14,19	10,28	11,9	10,97	14,75	9,846	11,41	13,13	18,65	14,66	14,56	13,68	8,943	10,46	12,66	13,82	11,12	9,989	15,28
TS41*	11,24	10,91	10,87	10,74	11,09	9,289	14,53	14,27	16,9	12,66	15,15	11,39	9,831	11,91	11,82	12,56	10,24	10,97	15,37
TS42	20,31	11,68	16,19	12,31	19,67	15,1	17,36	12,03	18,83	16,12	14,37	10,91	11,53	11,56	10,99	15	9,889	9,403	12,05
TS43	10,38	12,11	10,66	17,06	15,14	12,43	16,95	14,52	13,29	10,43	11,61	12	14,42	15,92	13,34	11,91	10,37	12,2	15,4
TS44	12,44	11,15	11,82	12,95	14,3	10,86	15,26	12,79	16,57	12,66	12,85	10,01	9,838	11	10,98	12,16	8,065	9,88	12,64
TS45	9,696	12,55	10,22	15,81	13,27	12,46	17,34	13,24	12,97	11,25	12,18	13,12	15,61	12,23	13,71	11,24	11,29	11,81	14,6
TS46	10,76	10,52	13,13	13,12	12,19	11,82	15,1	10,87	13,78	13,09	11,4	9,471	12,02	11,36	10,66	12,69	10,09	10,26	14,47
TS47	12,72	11,15	12,12	12,77	12,69	12,82	16,15	11,56	14,87	12,67	11,72	8,803	11,62	11,03	9,733	11,85	8,822	9,127	12,12
TS48	8,107	10,17	8,356	14,59	13,07	10,83	14,76	11,13	12,87	11,13	10,74	11,02	12,42	11,91	11,22	9,861	9,259	12,39	13,49
TS49	17,27	10,5	13,5	11,15	14,81	12,18	15,36	10,6	18,1	14,36	14,42	9,889	10,96	9,919	9,966	12,54	7,58	9,053	11,45
TS50	18,22	16,47	17,24	24,09	20,07	21,4	24,81	16,1	16,18	14	13,48	16,85	23,69	21,4	20,98	17,62	17,4	17,15	16,55

Table A.1: Pairwise average DTW matrix (Part 1). A cell inn the matrix provides the average distance between two participants. The highlighted rows and columns indicate hostile scenario participants. The matrix is symmetric, as both the rows and columns represent the same set of participants. Hence, the diagonal represent (average) genuine trials.

TS20	TS21*	TS22	TS23	TS24	TS25	TS26	TS27	TS28	TS29	TS30	TS31	TS32	TS33	TS34	TS35	TS36	TS37	TS38*	TS39	TS40	TS41*	TS42	TS43	TS44	TS45	TS46	TS47	TS48	TS49	TS50
12,7	12,74	15,19	12,19	13,18	12,37	10,29	10,96	11,65	17,69	8,341	13,59	15,3	13,69	12,58	11,24	20,56	14,6	21,8	10,26	14,19	11,24	20,31	10,38	12,44	9,696	10,76	12,72	8,107	17,27	18,22
15,65	10,12	10,44	10,2	10,66	11,65	12,72	12,22	12,8	10,35	11,26	11,38	8,758	10,32	13,05	10,53	13,36	11,5	17,44	9,311	10,28	10,91	11,68	12,11	11,15	12,55	10,52	11,15	10,17	10,5	16,47
11,03	12,89	12,8	12,13	11,34	11,43	13,06	12,13	7,817	15,11	10,95	9,763	11,39	10,66	14,7	10,56	16,57	10,9	19,65	8,713	11,9	10,87	16,19	10,66	11,82	10,22	13,13	12,12	8,356	13,5	17,24
19,24	14,17	14,35	14,46	16,85	14,33	19,13	16,46	12,96	12,79	16,84	14,44	12,03	11,56	16,05	13,08	13,59	17,06	14,7	13,32	10,97	10,74	12,31	17,06	12,95	15,81	13,12	12,77	14,59	11,15	24,09
15,98	11,42	14,39	14,41	13,44	12,09	13,69	11,93	15,6	16,96	11,94	13,92	13,83	13,98	13,01	9,779	18,22	16,24	20,4	11,58	14,75	11,09	19,67	15,14	14,3	13,27	12,19	12,69	13,07	14,81	20,07
15,59	13,65	14,97	14,38	15,34	10,46	15,93	13,32	10,59	11,15	13,22	12,67	13,97	9,643	14,43	10,12	15,5	14,49	17,67	11,94	9,846	9,289	15,1	12,43	10,86	12,46	11,82	12,82	10,83	12,18	21,4
20,92	18,96	18,23	16,51	19,43	14,59	19,47	16,82	14,04	15,19	18,72	19,03	17,65	14,55	17,78	13,74	15,82	18,7	19,42	16,33	11,41	14,53	17,36	16,95	15,26	17,34	15,1	16,15	14,76	15,36	24,81
14,38	14,13	11,8	8,312	10,77	14,47	15,5	14,18	14,37	10,62	13,27	13,83	11,74	13,41	12,83	12,49	13,12	11,57	18,34	9,656	13,13	14,27	12,03	14,52	12,79	13,24	10,87	11,56	11,13	10,6	16,1
12,56	13,09	13,79	13,19	9,705	14,87	7,417	10,71	16,08	16,29	8,72	13,96	15,78	16,94	16,09	14,8	23,13	12,98	24,12	12,93	18,65	16,9	18,83	13,29	16,57	12,97	13,78	14,87	12,87	18,1	16,18
10,49	12,97	11,71	11,75	8,988	12,89	13,12	12,42	11,47	13,56	9,972	10,04	11,35	10,98	15,59	11,72	18,18	9,689	23,17	10,25	14,66	12,66	16,12	10,43	12,66	11,25	13,09	12,67	11,13	14,36	14
10,76	13,22	10,28	9,199	7,681	13,08	11,12	10,77	13,6	15,08	10,08	10,65	11,71	14,55	13,46	12	16,09	10,23	19,92	9,687	14,56	15,15	14,37	11,61	12,85	12,18	11,4	11,72	10,74	14,42	13,48
12,28	8,714	7,367	9,59	10,92	11,41	13,1	11,27	13,02	8,506	10,2	12,07	8,611	10,81	11,24	10,74	13,81	11,6	16,4	10,28	13,68	11,39	10,91	12	10,01	13,12	9,471	8,803	11,02	9,889	16,85
18,85	13,31	12,28	13,74	16,04	12,28	18,41	15,55	12,47	12,1	15,63	12,81	10,77	9,741	16,7	10,82	12,74	16,2	14	11,88	8,943	9,831	11,53	14,42	9,838	15,61	12,02	11,62	12,42	10,96	23,69
19,82	14,48	13,44	12,69	16,89	15,26	17,46	14,51	11,03	11,11	16,43	14,77	12,93	11,77	15,57	12,92	12,83	16,62	15,24	12,17	10,46	11,91	11,56	15,92	11	12,23	11,36	11,03	11,91	9,919	21,4
12,69	11,45	9,742	9,896	12,32	13,63	16,32	13,07	13,53	8,562	12,46	12,67	9,807	11,86	11,8	11,21	12,68	12,74	15,24	10,46	12,66	11,82	10,99	13,34	10,98	13,71	10,66	9,733	11,22	9,966	20,98
12,08	12,15	10,98	10,54	9,448	12,87	13,42	12,78	11,8	13,04	10,29	9,353	10,61	12,5	15,24	11,05	16,48	10,79	19,33	8,68	13,82	12,56	15	11,91	12,16	11,24	12,69	11,85	9,861	12,54	17,62
14,42	10,02	8,152	9,057	12,38	13,48	15,26	11,9	9,397	7,266	10,84	10,67	7,496	9,319	13,88	13,04	12,82	12,22	15,86	7,892	11,12	10,24	9,889	10,37	8,065	11,29	10,09	8,822	9,259	7,58	17,4
14,37	9,5	9,89	9,53	10,89	10,27	15,11	11,34	12,64	10,4	12,08	10,77	8,297	9,976	12,26	9,011	11,96	12,24	15,37	8,989	9,989	10,97	9,403	12,2	9,88	11,81	10,26	9,127	12,39	9,053	17,15
12,27	14,23	11,87	11,13	11,5	16,13	16,94	15,3	15,47	11,52	14,14	10,39	12,37	15,25	14,93	16,52	14,8	13,31	18,36	10,17	15,28	15,37	12,05	15,4	12,64	14,6	14,47	12,12	13,49	11,45	16,55
2,327	16,76	10,78	14,87	9,823	13,24	14,52	12,84	12,88	18,82	12,66	11,72	12,79	17,93	13,61	15,43	19,72	13,5	23,49	13,51	19,29	18,46	17,23	13,2	18,09	12,87	17,19	15,42	14,77	19,35	13,07
16,76	4,023	10,68	13,06	13,39	12,41	13,61	11,16	16,8	11,3	10,57	12,93	9,301	11,2	15,24	11,85	18,31	14,69	19,98	11,93	16,22	11,69	13,62	14,91	13,49	14,88	12,57	11,69	13,91	11,79	17,35
10,78	10,68	3,125	10,54	10,58	12,04	15,36	12,73	16,05	8,656	12,06	9,397	7,09	11,89	12,86	11,91	14,04	13,87	17,6	10,4	13,53	12,51	11,09	13,26	9,398	15,2	10,22	9,091	11,14	11,29	18,19
14,87	13,06	10,54	3,995	10,34	15,34	14,75	13,79	11,93	10,21	11,49	12,99	10,46	12,26	13,16	12,82	13	10,91	18,28	8,283	11,73	13,01	12	12,42	10,82	12,16	8,522	10,51	8,161	10,46	16,65
9,823	13,39	10,58	10,34	4,117	13,29	12,57	12,15	13,85	14,92	10,04	10,17	12,09	14,84	14,36	11,73	17,74	10,07	22,44	9,765	14,82	14,85	16,03	11,96	14,21	12,29	13,01	12,32	11,8	15,26	12,51
13,24	12,41	12,04	15,34	13,29	4,308	13,59	10,11	12,68	12,74	11,27	12,67	12,75	12,3	14,86	9,121	15,7	13,94	18,28	12,71	14,06	11,62	15,02	9,973	12,21	13,38	12,94	11,6	13,68	14,59	19,11
14,52	13,61	15,36	14,75	12,57	13,59	3,664	10,65	14,88	14,89	8,972	14,83	16,8	17,49	16,92	14,58	21,75	14,75	24,86	12,64	18,34	16,08	20,83	13,98	16,85	11,79	13,45	14,89	11,61	16,96	17,23
12,84	11,16	12,73	13,79	12,15	10,11	10,65	4,713	12,98	12,41	8,584	13,26	13,36	13,83	12,44	10,28	18,96	14,22	22,26	11,34	16,22	13,97	17,13	11,65	13,69	10,17	11,24	11,27	12,04	12,76	18,69
12,88	16,8	16,05	11,93	13,85	12,68	14,88	12,98	3,758	12,59	12,73	11,88	15,05	12,01	15,32	14,27	16,18	13,71	18,38	10,38	9,948	11,6	15,56	11,27	10,62	10,05	11,05	12,94	8,705	12,92	18,54
18,82	11,3	8,656	10,21	14,92	12,74	14,89	12,41	12,59	2,91	12,15	12,65	9,11	11,09	12,87	16,97	10,86	12,6	14,49	8,687	11,72	11,13	9,179	10,11	8,179	10,69	10,59	9,755	9,352	8,493	17,98
12,66	10,57	12,06	11,49	10,04	11,27	8,972	8,584	12,73	12,15	2,977	12,56	11,91	13,32	13,72	11,99	18,95	12,63	22,03	10,64	16,21	12,72	19,29	9,797	14,24	10,22	11,81	12,14	9,534	15,02	17,75
11,72	12,93	9,397	12,99	10,17	12,67	14,83	13,26	11,88	12,65	12,56	4,435	9,779	13,85	14,9	13,05	16,24	13,79	19,87	10,06	13,87	14,61	13,86	13,2	13,16	12,06	15,49	13,11	12,73	13,35	16,05
12,79	9,301	7,09	10,46	12,09	12,75	16,8	13,36	15,05	9,11	11,91	9,779	3,832	8,052	12,35	12,81	12,43	12,41	15,69	10,39	11,12	11,38	9,507	13,44	10,02	15,05	11,24	10,45	11,24	8,912	20,04
17,93	11,2	11,89	12,26	14,84	12,3	17,49	13,83	12,01	11,09	13,32	13,85	8,052	4,724	14,14	11,67	12,72	12,85	15,04	12,86	10,27	9,859	10,44	12,95	11,01	14,48	11,36	12,13	13,15	9,722	19,56
13,61	15,24	12,86	13,16	14,36	14,86	16,92	12,44	15,32	12,87	13,72	14,9	12,35	14,14	5,353	11,85	13,12	15,33	19,49	14,31	14,41	15,55	15,28	14,21	14,28	12,64	10,65	11,96	13,36	12,14	18,46
15,43	11,85	11,91	12,82	11,73	9,121	14,58	10,28	14,27	16,97	11,99	13,05	12,81	11,67	11,85	3,901	14,88	14,13	19,32	11,03	11,82	11,91	18,63	11,87	12,21	12,56	11,46	10,58	12,1	13,43	20,14
19,72	18,31	14,04	13	17,74	15,7	21,75	18,96	16,18	10,86	18,95	16,24	12,43	12,72	13,12	14,88	5,553	15,63	11,84	15,19	9,868	15,14	9,617	16,67	11,71	16,9	13,07	13,03	16,01	10,6	21,74
13,5	14,69	13,87	10,91	10,07	13,94	14,75	14,22	13,71	12,6	12,63	13,79	12,41	12,85	15,33	14,13	15,63	4,025	20,2	12,31	14,52	15,79	14,31	12,52	14,84	13,32	13,9	14,64	12,38	14,54	12,29
23,49	19,98	17,6	18,28	22,44	18,28	24,86	22,26	18,38	14,49	22,03	19,87	15,69	15,04	19,49	19,32	11,84	20,2	8,332	17,73	14,14	16,24	12,07	21,57	15,24	19,71	17,61	16,37	18,99	13,61	25,93
13,51	11,93	10,4	8,283	9,765	12,71	12,64	11,34	10,38	8,687	10,64	10,06	10,39	12,86	14,31	11,03	15,19	12,31	17,73	5,239	12,31	11,77	14,33	11,5	10,05	10,13	9,828	9,826	7,47	9,929	18,33
19,29	16,22	13,53	11,73	14,82	14,06	18,34	16,22	9,948	11,72	16,21	13,87	11,12	10,27	14,41	11,82	9,868	14,52	14,14	12,31	3,331	11,58	10,48	12,72	11,6	14,25	11,62	13,54	11,5	10,92	20,78
18,46	11,69	12,51	13,01	14,85	11,62	16,08	13,97	11,6	11,13	12,72	14,61	11,38	9,859	15,55	11,91	15,14	15,79	16,24	11,77	11,58	4,603	14,04	12,76	9,135	13,51	9,026	10,08	10,49	11,76	22,28
17,23	13,62	11,09	12	16,03	15,02	20,83	17,13	15,56	9,179	19,29	13,86	9,507	10,44	15,28	18,63	9,617	14,31	12,07	14,33	10,48	14,04	3,965	16,15	10,37	16,64	14,61	12,04	17,83	9,092	19,38
13,2	14,91	13,26	12,42	11,96	9,973	13,98	11,65	11,27	10,11	9,797	13,2	13,44	12,95	14,21	11,87	16,67	12,52	21,57	11,5	12,72	12,76	16,15	4,199	11,17	12,01	11,37	13,16	10,08	16,26	17,77
18,09	13,49	9,398	10,82	14,21	12,21	16,85	13,69	10,62	8,179	14,24	13,16	10,02	11,01	14,28	12,21	11,71	14,84	15,24	10,05	11,6	9,135	10,37	11,17	3,755	13,8	8,25	8,365	10,25	10,23	19,36
12,87	14,88	15,2	12,16	12,29	13,38	11,79	10,17	10,05	10,69	10,22	12,06	15,05	14,48	12,64	12,56	16,9	13,32	19,71	10,13	14,25	13,51	16,64	12,01	13,8	7,893	11,03	12,09	8,935	11,23	18,05
17,19	12,57	10,22	8,522	13,01	12,94	13,45	11,24	11,05	10,59	11,81	15,49	11,24	11,36	10,65	11,46	13,07	13,9	17,61	9,828	11,62	9,026	14,61	11,37	8,25	11,03	3,998	8,224	8,677	10,81	18,69
15,42	11,69	9,091	10,51	12,32	11,6	14,89	11,27	12,94	9,755	12,14	13,11	10,45	12,13	11,96	10,58	13,03	14,64	16,37	9,826	13,54	10,08	12,04	13,16	8,365	12,09	8,224	5,846	12,7	10,04	19,04
14,77	13,91	11,14	8,161	11,8	13,68	11,61	12,04	8,705	9,352	9,534	12,73	11,24	13,15	13,36	12,1	16,01	12,38	18,99	7,47	11,5	10,49	17,83	10,08	10,25	8,935	8,677	12,7	3,214	12,99	20,01
19,35	11,79	11,29	10,46	15,26	14,59	16,96	12,76	12,92	8,493	15,02	13,35	8,912	9,722	12,14	13,43	10,6	14,54	13,61	9,929	10,92	11,76	9,092	16,26	10,23	11,23	10,81	10,04	12,99	5,413	18,95
13,07	17,35	18,19	16,65	12,51	19,11	17,23	18,69	18,54	17,98	17,75	16,05	20,04	19,56	18,46	20,14	21,74	12,29	25,93	18,33	20,78	22,28	19,38	17,77	19,36	18,05	18,69	19,04	20,01	18,95	3,314

Table A.2: Pairwise average DTW matrix (Part 2). A cell inn the matrix provides the average distance between two participants. The highlighted rows and columns indicate hostile scenario participants. The matrix is symmetric, as both the rows and columns represent the same set of participants. Hence, the diagonal represent (average) genuine trials.

	TS01	TS02	TS03*	TS04*	TS05	TS06	TS07	TS08	TS09	TS10	TS11	TS12	TS13	TS14	TS15	TS16	TS17	TS18*	TS19
TS01	1,358	0,992	0,634	1,079	1,387	0,96	1,684	2,769	1,409	0,844	0,812	2,495	1,547	1,938	2,863	0,501	2,846	1,054	1,454
TS02	0,992	1,288	0,773	1,385	0,877	1,295	2,547	1,402	1,186	0,865	1,091	0,554	1,567	1,639	1,722	0,926	0,721	0,747	0,852
TS03*	0,634	0,773	1,196	1,439	0,829	1,286	2,464	3,297	1,033	0,939	0,756	2,351	1,346	2,158	3,897	0,754	2,861	0,858	1,523
TS04*	1,079	1,385	1,439	3,863	2,176	1,298	2,67	2,148	1,359	1,645	1,534	1,675	1,38	2,356	2,192	1,689	1,848	1,249	2,78
TS05	1,387	0,877	0,829	2,176	1,607	1,261	2,034	1,685	1,497	0,953	1,256	1,809	1,128	1,29	1,578	1,009	2,228	0,602	1,776
TS06	0,96	1,295	1,286	1,298	1,261	2,083	1,984	1,732	1,445	1,344	1,335	2,067	1,61	1,393	2,382	1,354	1,514	1,25	1,349
TS07	1,684	2,547	2,464	2,67	2,034	1,984	2,595	2,29	1,934	2,347	2,209	1,54	2,191	2,371	2,879	2,696	2,702	1,899	2,017
TS08	2,769	1,402	3,297	2,148	1,685	1,732	2,29	2,784	2,565	4,419	2,219	1,268	2,02	2,006	2,713	2,507	1,278	1,235	1,782
TS09	1,409	1,186	1,033	1,359	1,497	1,445	1,934	2,565	1,434	0,866	1,031	1,638	1,646	1,901	4,133	1,177	1,636	1,23	2,238
TS10	0,844	0,865	0,939	1,645	0,953	1,344	2,347	4,419	0,866	1,604	0,677	2,166	1,841	1,952	4,465	1,038	2,915	0,981	2,391
TS11	0,812	1,091	0,756	1,534	1,256	1,335	2,209	2,219	1,031	0,677	1,455	2,05	1,535	1,772	4,344	0,905	1,438	1,214	1,425
TS12	2,495	0,554	2,351	1,675	1,809	2,067	1,54	1,268	1,638	2,166	2,05	1,544	1,328	1,572	2,148	1,221	1,17	0,77	1,362
TS13	1,547	1,567	1,346	1,38	1,128	1,61	2,191	2,02	1,646	1,841	1,535	1,328	1,755	1,887	1,366	1,553	1,871	1,108	2,004
TS14	1,938	1,639	2,158	2,356	1,29	1,393	2,371	2,006	1,901	1,952	1,772	1,572	1,887	3,491	1,854	1,84	1,778	1,308	2,016
TS15	2,863	1,722	3,897	2,192	1,578	2,382	2,879	2,713	4,133	4,465	4,344	2,148	1,366	1,854	3,907	3,071	1,875	1,179	2,641
TS16	0,501	0,926	0,754	1,689	1,009	1,354	2,696	2,507	1,177	1,038	0,905	1,221	1,553	1,84	3,071	1,749	2,197	1,064	1,917
TS17	2,846	0,721	2,861	1,848	2,228	1,514	2,702	1,278	1,636	2,915	1,438	1,17	1,871	1,778	1,875	2,197	1,901	0,825	1,212
TS18*	1,054	0,747	0,858	1,249	0,602	1,25	1,899	1,235	1,23	0,981	1,214	0,77	1,108	1,308	1,179	1,064	0,825	1,177	0,935
TS19	1,454	0,852	1,523	2,78	1,776	1,349	2,017	1,782	2,238	2,391	1,425	1,362	2,004	2,016	2,641	1,917	1,212	0,935	2,677
TS20	0,556	0,689	0,819	2,409	0,783	1,336	2,577	3,035	0,888	1,3	0,755	1,614	1,121	2,774	3,76	1,52	2,013	0,882	2,176
TS21*	3,213	1,152	3,412	1,923	1,723	1,843	1,982	1,348	2,29	2,92	1,844	0,678	1,914	1,601	1,709	2,449	0,994	1,113	1,077
TS22	1,125	0,605	0,926	1,531	0,804	1,061	2,168	0,875	1,158	1,276	1,17	0,763	1,508	2,201	2,086	1,709	0,864	0,749	0,735
TS23	2,871	0,788	2,344	1,338	1,255	2,09	2,23	1,346	2,031	2,604	1,862	0,99	1,279	2,049	2,323	1,501	1,07	0,726	1,226
TS24	1,031	1,139	1,116	2,134	1,25	1,166	2,524	3,17	1,006	1,02	0,9	1,681	1,667	2,075	4,791	1,168	1,887	1,481	1,677
TS25	0,741	0,827	1,025	1,393	0,928	1,481	1,582	1,662	1,051	0,762	1,094	1,892	1,126	1,329	2,27	1,047	1,461	0,879	0,901
TS26	1,164	1,333	1,028	1,412	1,423	1,663	1,624	3,201	0,801	0,749	0,596	2,134	1,722	2,063	2,904	0,794	1,99	1,295	1,67
TS27	1,498	1,001	0,89	1,873	1,428	2,125	1,752	3,041	1,438	0,953	0,892	2,553	1,739	2,424	3,21	1,17	2,502	1,313	2,318
TS28	0,71	1,12	0,763	1,603	1,431	1,059	2	2,539	1,393	1,34	0,816	2,232	1,496	1,455	3,233	1,4	2,417	0,947	1,566
TS29	2,085	1,102	1,39	1,821	2,832	1,192	3,448	1,753	2,381	2,426	1,785	1,298	1,622	1,572	1,812	2,224	1,218	0,737	1,155
TS30	0,886	0,744	0,544	1,49	1,31	1,265	1,578	2,679	1,164	0,668	0,531	2,081	1,483	1,815	3,425	0,928	1,863	0,955	1,514
TS31	1,152	1,589	1,61	2,401	0,953	1,529	3,053	3,101	1,434	2,052	1,123	1,431	1,353	2,383	2,907	1,818	2,404	1,247	1,571
TS32	1,322	0,917	1,388	1,941	1,849	0,982	2,345	1,329	1,728	1,975	1,513	0,98	1,582	2,122	1,875	1,493	1,106	0,722	1,456
TS33	2,13	0,953	2,405	1,855	0,794	1,326	1,995	1,265	1,456	1,827	1,218	1,211	1,845	1,654	1,138	1,6	1,01	0,85	1,341
TS34	2,764	1,455	1,445	3,078	1,535	2,016	2,167	1,624	1,64	1,504	1,412	1,519	2,505	2,557	2,285	1,435	1,657	1,409	2,109
TS35	1,126	0,82	0,854	1,41	0,972	1,421	1,649	2,095	1,414	0,96	1,279	1,637	1,119	1,923	1,134	0,997	1,93	0,781	2,131
TS36	1,684	3,005	2,419	1,776	1,924	2,137	3,17	3,141	2,377	3,586	2,791	1,761	1,796	2,626	1,929	3,132	1,95	2,312	2,362
TS37	0,617	1,473	1,218	1,833	1,962	1,607	2,481	2,38	0,778	0,944	0,742	1,175	1,814	1,739	2,38	1,088	1,299	1,638	1,242
TS38*	2,952	3,651	3,88	3,879	1,935	2,579	2,966	4,111	3,477	4,971	3,771	3,778	3,952	4,054	4,18	4,237	4,383	3,684	4,261
TS39	0,939	1,152	1,51	1,576	1,193	1,573	2,017	1,574	1,257	1,357	1,145	1,125	1,489	2,133	3,199	1,524	0,847	0,894	1,36
TS40	1,047	1,151	1,064	1,539	1,328	1,001	2,488	1,619	1,208	1,297	1,326	0,755	0,753	1,444	0,709	1,218	1,218	0,918	1,224
TS41*	1,292	1,167	1,304	2,021	1,381	0,96	2,426	1,754	1,651	1,52	1,418	1,28	1,438	1,377	1,703	1,315	1,454	1,384	1,72
TS42	1,344	1,05	1,925	1,309	2,913	0,801	4,228	1,48	1,027	2,365	1,575	1,023	0,966	2,954	1,332	2,219	1,22	0,774	1,579
TS43	0,792	1,247	1,09	1,501	1,399	1,237	2,193	2,662	1,434	1,366	1,09	1,987	1,618	1,485	2,845	1,689	1,977	1,194	1,51
TS44	1,207	0,9	1,189	1,993	1,404	1,184	2,342	1,862	1,456	1,196	1,18	1,03	1,216	1,89	1,088	0,872	1,329	0,783	1,289
TS45	2,219	2,475	1,024	3,645	1,775	2,429	2,998	2,771	3,342	2,142	1,862	2,851	3,572	2,976	3,7	1,723	3,061	2,041	2,468
TS46	1,092	0,698	1,274	2,044	1,337	1,365	2,134	1,5	1,671	1,06	1,164	0,819	1,642	2,089	1,361	0,768	1,434	0,971	1,983
TS47	3,489	2,23	3,886	2,076	1,705	1,796	2,147	2,133	3,863	3,453	3,22	2,001	1,743	1,721	1,708	3,086	1,57	1,789	2,078
TS48	0,747	1,511	0,888	1,734	0,847	1,116	1,554	1,84	1,535	0,966	1,285	1,357	1,387	1,982	3,065	0,99	1,303	1,342	1,4
TS49	2,875	1,806	3,995	1,947	1,418	1,349	2,588	2,283	2,337	3,822	2,345	1,018	1,494	1,852	1,697	3,298	1,572	1,266	1,739
TS50	1,972	1,06	1,222	1,907	1,097	1,17	1,913	2,205	2,364	1,215	1,552	3,571	2,014	1,678	3,702	2,552	2,142	1,983	2,635

Table A.3: Pairwise STD matrix (Part 1). A cell inn the matrix provides the standard deviation in the distance between two participants. The highlighted rows and columns indicate hostile scenario participants.

TS20	TS21*	TS22	TS23	TS24	TS25	TS26	TS27	TS28	TS29	TS30	TS31	TS32	TS33	TS34	TS35	TS36	TS37	TS38*	TS39	TS40	TS41*	TS42	TS43	TS44	TS45	TS46	TS47	TS48	TS49	TS50
0,556	3,213	1,125	2,871	1,031	0,741	1,164	1,498	0,71	2,085	0,886	1,152	1,322	2,13	2,764	1,126	1,684	0,617	2,952	0,939	1,047	1,292	1,344	0,792	1,207	2,219	1,092	3,489	0,747	2,875	1,972
0,689	1,152	0,605	0,788	1,139	0,827	1,333	1,001	1,12	1,102	0,744	1,589	0,917	0,953	1,455	0,82	3,005	1,473	3,651	1,152	1,151	1,167	1,05	1,247	0,9	2,475	0,698	2,23	1,511	1,806	1,06
0,819	3,412	0,926	2,344	1,116	1,025	1,028	0,89	0,763	1,39	0,544	1,61	1,388	2,405	1,445	0,854	2,419	1,218	3,88	1,51	1,064	1,304	1,925	1,09	1,189	1,024	1,274	3,886	0,888	3,995	1,222
2,409	1,923	1,531	1,338	2,134	1,393	1,412	1,873	1,603	1,821	1,49	2,401	1,941	1,855	3,078	1,41	1,776	1,833	3,879	1,576	1,539	2,021	1,309	1,501	1,993	3,645	2,044	2,076	1,734	1,947	1,907
0,783	1,723	0,804	1,255	1,25	0,928	1,423	1,428	1,431	2,832	1,31	0,953	1,849	0,794	1,535	0,972	1,924	1,962	1,935	1,193	1,328	1,381	2,913	1,399	1,404	1,775	1,337	1,705	0,847	1,418	1,097
1,336	1,843	1,061	2,09	1,166	1,481	1,663	2,125	1,059	1,192	1,265	1,529	0,982	1,326	2,016	1,421	2,137	1,607	2,579	1,573	1,001	0,96	0,801	1,237	1,184	2,429	1,365	1,796	1,116	1,349	1,17
2,577	1,982	2,168	2,23	2,524	1,582	1,624	1,752	2	3,448	1,578	3,053	2,345	1,995	2,167	1,649	3,17	2,481	2,966	2,017	2,488	2,426	4,228	2,193	2,342	2,998	2,134	2,147	1,554	2,588	1,913
3,035	1,348	0,875	1,346	3,17	1,662	3,201	3,041	2,539	1,753	2,679	3,101	1,329	1,265	1,624	2,095	3,141	2,38	4,111	1,574	1,619	1,754	1,48	2,662	1,862	2,771	1,5	2,133	1,84	2,283	2,205
0,888	2,29	1,158	2,031	1,006	1,051	0,801	1,438	1,393	2,381	1,164	1,434	1,728	1,456	1,64	1,414	2,377	0,778	3,477	1,257	1,208	1,651	1,027	1,434	1,456	3,342	1,671	3,863	1,535	2,337	2,364
1,3	2,92	1,276	2,604	1,02	0,762	0,749	0,953	1,34	2,426	0,668	2,052	1,975	1,827	1,504	0,96	3,586	0,944	4,971	1,357	1,297	1,52	2,365	1,366	1,196	2,142	1,06	3,453	0,966	3,822	1,215
0,755	1,844	1,17	1,862	0,9	1,094	0,596	0,892	0,816	1,785	0,531	1,123	1,513	1,218	1,412	1,279	2,791	0,742	3,771	1,145	1,326	1,418	1,575	1,09	1,18	1,862	1,164	3,22	1,285	2,345	1,552
1,614	0,678	0,763	0,99	1,681	1,892	2,134	2,553	2,232	1,298	2,081	1,431	0,98	1,211	1,519	1,637	1,761	1,175	3,778	1,125	0,755	1,28	1,023	1,987	1,03	2,851	0,819	2,001	1,357	1,018	3,571
1,121	1,914	1,508	1,279	1,667	1,126	1,722	1,739	1,496	1,622	1,483	1,353	1,582	1,845	2,505	1,119	1,796	1,814	3,952	1,489	0,753	1,438	0,966	1,618	1,216	3,572	1,642	1,743	1,387	1,494	2,014
2,774	1,601	2,201	2,049	2,075	1,329	2,063	2,424	1,455	1,572	1,815	2,383	2,122	1,654	2,557	1,923	2,626	1,739	4,054	2,133	1,444	1,377	2,954	1,485	1,89	2,976	2,089	1,721	1,982	1,852	1,678
3,76	1,709	2,086	2,323	4,791	2,27	2,904	3,21	3,233	1,812	3,425	2,907	1,875	1,138	2,285	1,134	1,929	2,38	4,18	3,199	0,709	1,703	1,332	2,845	1,088	3,7	1,361	1,708	3,065	1,697	3,702
1,52	2,449	1,709	1,501	1,168	1,047	0,794	1,17	1,4	2,224	0,928	1,818	1,493	1,6	1,435	0,997	3,132	1,088	4,237	1,524	1,218	1,315	2,219	1,689	0,872	1,723	0,768	3,086	0,99	3,298	2,552
2,013	0,994	0,864	1,07	1,887	1,461	1,99	2,502	2,417	1,218	1,863	2,404	1,106	1,01	1,657	1,93	1,95	1,299	4,383	0,847	1,218	1,454	1,22	1,977	1,329	3,061	1,434	1,57	1,303	1,572	2,142
0,882	1,113	0,749	0,726	1,481	0,879	1,295	1,313	0,947	0,737	0,955	1,247	0,722	0,85	1,409	0,781	2,312	1,638	3,684	0,894	0,918	1,384	0,774	1,194	0,783	2,041	0,971	1,789	1,342	1,266	1,983
2,176	1,077	0,735	1,226	1,677	0,901	1,67	2,318	1,566	1,155	1,514	1,571	1,456	1,341	2,109	2,131	2,362	1,242	4,261	1,36	1,224	1,72	1,579	1,51	1,289	2,468	1,983	2,078	1,4	1,739	2,635
0,955	3,526	0,661	1,368	0,78	1,475	1,584	0,888	0,921	1,29	1,363	1,129	1,486	1,252	2,302	0,77	2,907	1,085	3,8	1,554	1,084	2,255	2,165	2,571	1,091	3,474	0,738	4,103	1,81	3,459	0,553
3,526	1,69	0,983	1,158	2,568	2,386	1,684	2,345	1,847	0,698	2,55	2,355	1,196	1,508	1,909	1,358	2,076	1,551	4,111	1,208	1,106	1,572	1,418	2,087	1,137	3,782	0,771	2,086	1,486	1,127	1,738
0,661	0,983	1,245	0,577	1,126	1,288	1,304	1,269	0,979	1,28	1,593	0,605	1,029	1,068	1,497	1,227	2,466	0,928	4,463	1,153	1,093	1,377	1,783	1,483	1,113	2,474	1,086	2,284	1,777	1,658	1,884
1,368	1,158	0,577	1,806	2,257	1,105	2,489	2,47	2,921	1,889	2,003	2,167	1,145	0,822	1,793	1,325	2,685	1,346	3,537	1,159	1,024	1,301	0,937	1,934	0,868	3,143	0,985	2,06	1,315	2,015	2,474
0,78	2,568	1,126	2,257	1,904	0,916	0,83	0,996	1,08	1,814	0,661	1,466	1,892	1,285	1,442	1,236	3,259	0,898	4,131	1,488	1,733	1,712	1,908	1,264	1,175	2,767	0,892	3,902	1,48	2,934	1,903
1,475	2,386	1,288	1,105	0,916	2,164	1,115	1,53	1,177	1,352	0,841	1,126	0,975	0,964	1,493	0,97	2,385	0,972	2,818	1,398	0,793	1,715	0,904	1,076	0,955	1,813	1,112	2,639	0,755	1,437	1,004
1,584	1,684	1,304	2,489	0,83	1,115	1,904	1,453	1,218	1,914	0,772	1,142	1,66	1,693	1,78	1,314	1,789	1,285	2,941	1,068	1,297	1,829	1,134	1,208	1,569	3,047	1,59	2,871	1,365	1,855	1,554
0,888	2,345	1,269	2,47	0,996	1,53	1,453	1,999	1,484	1,781	1,178	1,319	2,052	1,885	1,417	1,423	2,402	1,367	3,172	1,624	1,512	1,522	3,156	1,33	1,531	2,685	0,972	2,061	1,842	1,64	1,497
0,921	1,847	0,979	2,921	1,08	1,177	1,218	1,484	1,534	2,8	0,765	1,906	0,957	1,481	1,844	1,198	1,982	0,934	3,736	1,41	1,323	0,928	1,074	0,874	0,694	1,368	0,831	2,602	0,741	3,431	0,808
1,29	0,698	1,28	1,889	1,814	1,352	1,914	1,781	2,8	1,399	1,118	2,144	1,044	1,008	2,095	1,959	1,809	0,996	3,404	1,224	0,934	1,38	1,182	1,553	1,298	1,332	2,728	1,559	1,043	1,017	2,642
1,363	2,55	1,593	2,003	0,661	0,841	0,772	1,178	0,765	1,118	1,103	1,519	2,019	1,919	1,991	1,171	2,621	0,882	3,435	0,874	1,124	1,574	1,631	1,18	1,188	2,797	1,187	3,565	0,642	3,518	3,065
1,129	2,355	0,605	2,167	1,466	1,126	1,142	1,319	1,906	2,144	1,519	1,71	1,491	1,664	1,942	1,076	2,769	1,328	4,223	2,007	1,271	1,956	2,503	2,438	1,759	2,006	1,519	2,49	2,376	3,169	1,377
1,486	1,196	1,029	1,145	1,892	0,975	1,66	2,052	0,957	1,044	2,019	1,491	1,714	1,038	2,324	1,45	2,702	1,62	4,699	1,252	1,039	1,567	1,594	1,414	0,929	2,831	1,192	1,392	1,945	1,266	2,106
1,252	1,508	1,068	0,822	1,285	0,964	1,693	1,885	1,481	1,008	1,919	1,664	1,038	2,237	2,75	0,968	2,204	1,89	4,546	1,075	1,299	1,183	0,631	1,49	0,791	3,271	1,188	1,377	1,286	1,102	1,831
2,302	1,909	1,497	1,793	1,442	1,493	1,78	1,417	1,844	2,095	1,991	1,942	2,324	2,75	2,769	1,375	3,185	1,502	3,405	2,181	2,132	2,02	4,489	2,076	2,677	2,011	1,122	2,15	1,823	1,46	1,23
0,77	1,358	1,227	1,325	1,236	0,97	1,314	1,423	1,198	1,959	1,171	1,076	1,45	0,968	1,375	1,582	2,665	1,923	2,553	1,275	1,347	1,177	4,369	1,387	1,176	1,679	1,265	2,328	1,003	1,814	1,787
2,907	2,076	2,466	2,685	3,259	2,385	1,789	2,402	1,982	1,809	2,621	2,769	2,702	2,204	3,185	2,665	3,06	2,752	3,097	3,341	1,999	1,876	1,632	3,089	1,846	2,837	2,08	1,989	3,423	2,053	2,935
1,085	1,551	0,928	1,346	0,898	0,972	1,285	1,367	0,934	0,996	0,882	1,328	1,62	1,89	1,502	1,923	2,752	2,085	4,081	1,173	1,825	1,442	1,515	1,105	1,237	1,557	1,066	2,709	0,934	2,98	1,495
3,8	4,111	4,463	3,537	4,131	2,818	2,941	3,172	3,736	3,404	3,435	4,223	4,699	4,546	3,405	2,553	3,097	4,081	4,831	3,647	2,829	4,044	3,887	3,978	4,035	3,917	3,363	3,879	3,346	3,91	3,788
1,554	1,208	1,153	1,159	1,488	1,398	1,068	1,624	1,41	1,224	0,874	2,007	1,252	1,075	2,181	1,275	3,341	1,173	3,647	2,201	1,154	1,229	2,293	1,241	1,372	2,696	1,167	2,375	1,18	1,975	2,148
1,084	1,106	1,093	1,024	1,733	0,793	1,297	1,512	1,323	0,934	1,124	1,271	1,039	1,299	2,132	1,347	1,999	1,825	2,829	1,154	1,37	1,212	0,646	1,284	1,012	3,322	1,01	1,214	1,04	1,093	1,256
2,255	1,572	1,377	1,301	1,712	1,715	1,829	1,522	0,928	1,38	1,574	1,956	1,567	1,183	2,02	1,177	1,876	1,442	4,044	1,229	1,212	1,863	1,591	1,111	1,214	3,273	1,147	1,488	0,9	1,234	1,951
2,165	1,418	1,783	0,937	1,908	0,904	1,134	3,156	1,074	1,182	1,631	2,503	1,594	0,631	4,489	4,369	1,632	1,515	3,887	2,293	0,646	1,591	1,604	2,369	0,912	3,171	3,877	2,891	0,981	1,187	1,861
2,571	2,087	1,483	1,934	1,264	1,076	1,208	1,33	0,874	1,553	1,18	2,438	1,414	1,49	2,076	1,387	3,089	1,105	3,978	1,241	1,284	1,111	2,369	1,858	1,127	2,049	0,759	3,517	0,752	3,073	2,427
1,091	1,137	1,113	0,868	1,175	0,955	1,569	1,531	0,694	1,298	1,188	1,759	0,929	0,791	2,677	1,176	1,846	1,237	4,035	1,372	1,012	1,214	0,912	1,127	1,518	3,429	1,137	1,645	1,056	1,043	2,043
3,474	3,782	2,474	3,143	2,767	1,813	3,047	2,685	1,368	1,332	2,797	2,006	2,831	3,271	2,011	1,679	2,837	1,557	3,917	2,696	3,322	3,273	3,171	2,049	3,429	3,845	1,962	2,736	2,908	2,243	2,153
0,738	0,771	1,086	0,985	0,892	1,112	1,59	0,972	0,831	2,728	1,187	1,519	1,192	1,188	1,122	1,265	2,08	1,066	3,363	1,167	1,01	1,147	3,877	0,759	1,137	1,962	1,753	2,133	0,823	1,252	2,556
4,103	2,086	2,284	2,06	3,902	2,639	2,871	2,061	2,602	1,559	3,565	2,49	1,392	1,377	2,15	2,328	1,989	2,709	3,879	2,375	1,214	1,488	2,891	3,517	1,645	2,736	2,133	3,576	2,385	1,504	3,205
1,81	1,486	1,777	1,315	1,48	0,755	1,365	1,842	0,741	1,043	0,642	2,376	1,945	1,286	1,823	1,003	3,423	0,934	3,346	1,18	1,04	0,9	0,981	0,752	1,056	2,908	0,823	2,385	1,266	2,797	1,708
3,459	1,127	1,658	2,015	2,934	1,437	1,855	1,64	3,431	1,017	3,518	3,169	1,266	1,102	1,46	1,814	2,053	2,98	3,91	1,975	1,093	1,234	1,187	3,073	1,043	2,243	1,252	1,504	2,797	2,861	2,358
0,553	1,738	1,884	2,474	1,903	1,004	1,554	1,497	0,808	2,642	3,065	1,377	2,106	1,831	1,23	1,787	2,935	1,495	3,788	2,148	1,256	1,951	1,861	2,427	2,043	2,153	2,556	3,205	1,708	2,358	1,965

Table A.4: Pairwise STD matrix (Part 2). A cell inn the matrix provides the standard deviation in the distance between two participants. The highlighted rows and columns indicate hostile scenario participants.

A.2 The Short-Term Hostile Scenario

Table A.5 shows a complete overview of DTW mimicking results, every WALK included. Table A.6 is an Euclidean version.

	S1GO1	S1GO2	S1GO3	S2GO1	S2GO2	S2GO3	S3GO1	S3GO2	S3GO3	S4GO1	S4GO2	S4GO3	S5GO1	S5GO2	S5GO3
TS03	10,92	13,05	10,89	12,29	10,68	12,28	10,37	10,79	12,00	11,60	12,15	11,58	12,83	11,06	10,57
	11,40	14,52	13,30	10,61	10,53	13,43	10,23	10,97	11,21	10,67	10,61	10,40	13,76	10,80	9,42
	12,02	13,45	13,48	10,56	10,28	11,91	10,88	11,90	11,64	9,85	12,12	10,33	13,62	11,35	9,24
	12,40	14,15	13,40	12,19	11,41	12,59	11,11	11,83	11,19	10,38	11,40	10,23	14,06	11,57	9,53
				12,09					10,52	11,39				10,80	
				11,22					11,43	10,45				11,42	
Mean	11,68	13,79	12,77	11,50	10,72	12,55	10,65	11,37	11,33	10,72	11,57	10,64	13,57	11,17	9,69
Median	11,71	13,80	13,35	11,66	10,60	12,44	10,63	11,40	11,32	10,56	11,76	10,37	13,69	11,20	9,47
TS04	13,53	12,41	11,41	11,92	10,81	11,99	15,85	10,85	7,16	12,68	14,14	12,25	14,43	12,07	12,11
	12,74	7,78	12,71	10,31	11,25	11,41	9,41	10,79	11,55	12,04	9,64	11,79	12,55	11,76	11,21
	14,39	9,51	11,52	11,47	9,89	10,34	12,19	10,26	12,51	12,41	9,70	11,53	12,57	10,18	11,56
	13,82	10,23	10,34	11,59	11,22	10,65	8,55	10,14	12,78	11,94	9,65	10,63	12,36	10,43	11,79
		10,37							11,71		12,62				
		12,17							11,39		10,47				
Mean	13,62	10,41	11,50	11,33	10,79	11,10	11,50	10,51	11,18	12,27	11,04	11,55	12,98	11,11	11,67
Median	13,68	10,30	11,46	11,53	11,01	11,03	10,80	10,52	11,63	12,22	10,09	11,66	12,56	11,10	11,68
TS18	11,61	9,80	10,43	11,20	10,58	9,78	8,92	8,49	7,64	8,52	9,91	9,99	8,95	8,76	9,25
	13,51	9,06	10,45	10,79	9,92	7,87	9,16	8,96	9,22	8,09	10,49	10,73	7,96	9,36	9,48
	12,40	9,33	9,74	10,98	9,47	8,87	8,60	9,12	9,14	7,73	9,35	13,67	7,68	9,48	9,54
	12,34	9,37	10,23	10,60	10,18	9,13	8,60	8,32	8,82	8,32	9,69	14,38	8,72	9,43	10,08
			9,88	10,92			8,53	9,30	8,52	8,18	9,98				
			9,99	11,09			8,89	8,74	8,66	7,78	9,68				
Mean	12,47	9,39	10,12	10,93	10,04	8,91	8,78	8,82	8,67	8,10	9,85	12,19	8,33	9,26	9,59
Median	12,37	9,35	10,11	10,95	10,05	9,00	8,75	8,85	8,74	8,13	9,80	12,20	8,34	9,40	9,51
TS21	11,64	13,03	12,57	10,15	12,58	12,03	11,38	11,69	16,72	13,17	13,72	12,17	11,07	12,11	12,76
	10,92	13,23	10,81	12,73	13,43	11,74	10,64	12,11	10,12	19,51	12,46	13,80	12,44	12,18	13,96
	9,99	12,11	11,25	13,50	12,77	12,38	20,64	12,13	11,05	15,24	13,63	14,43	12,24	13,80	13,82
	10,88	11,60	11,09	13,27	13,66	11,73	16,87	12,70	10,57	15,54	13,88	10,60	9,35	14,00	13,93
Mean	10,85	12,49	11,43	12,41	13,11	11,97	14,88	12,16	12,12	15,87	13,42	12,75	11,27	13,02	13,62
Median	10,90	12,57	11,17	13,00	13,10	11,89	14,13	12,12	10,81	15,39	13,68	12,99	11,65	12,99	13,88
TS38	10,02	8,96	7,83	9,42	9,80	9,80	11,27	10,36	11,49	9,83	10,66	9,89	11,58	10,25	12,82
	10,16	8,30	8,15	8,89	10,70	9,06	10,23	10,95	10,09	10,55	11,03	10,40	11,35	10,47	13,95
	8,16	8,10	8,46	8,90	11,76	9,33	11,12	11,51	11,02	19,19	11,53	11,11	13,12	8,61	11,42
	8,15	7,83	8,23	9,37	9,64	9,37	9,88	11,61	11,12	22,84	12,25	10,01	12,33	10,03	11,39
			9,87							20,12					
			9,33							15,32					
Mean	9,12	8,30	8,64	9,15	10,48	9,39	10,62	11,11	10,93	16,31	11,37	10,35	12,09	9,84	12,40
Median	9,09	8,20	8,34	9,14	10,25	9,35	10,67	11,23	11,07	17,26	11,28	10,20	11,96	10,14	12,12
TS41	12,36	11,13	12,65	11,10	11,42	10,78	10,94	10,79	13,13	11,33	11,95	11,31	7,98	9,55	11,41
	11,04	11,56	13,39	11,52	12,12	9,86	12,55	11,87	13,21	11,60	11,35	12,45	7,55	8,54	10,14
	11,19	11,51	12,98	11,36	10,90	10,52	11,78	12,25	13,43	11,86	12,55	12,03	9,32	9,78	9,01
	13,93	13,61	15,11	11,82	9,81	9,59	12,95	12,64	13,30	16,96	11,18	12,59	10,14	9,09	10,74
			14,24			11,12			10,76	11,73					
			14,27			9,78			12,02	11,93					
Mean	12,13	11,96	13,77	11,45	11,06	10,28	12,06	11,89	12,64	12,57	11,76	12,10	8,75	9,24	10,33
Median	11,77	11,54	13,81	11,44	11,16	10,19	12,17	12,06	13,17	11,80	11,65	12,24	8,65	9,32	10,44

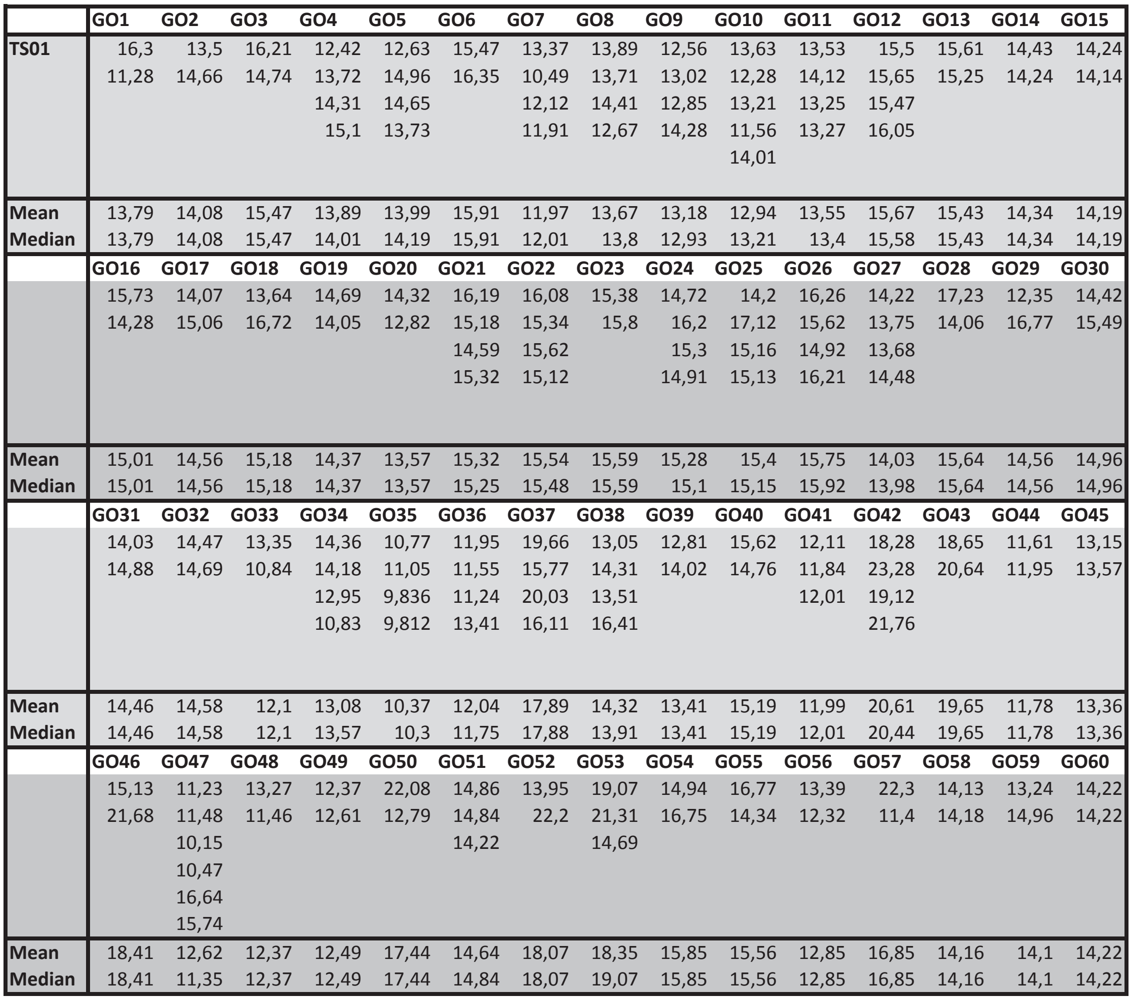
Table A.5: Short-term DTW mimicking results, full.

	S1GO1	S1GO2	S1GO3	S2GO1	S2GO2	S2GO3	S3GO1	S3GO2	S3GO3	S4GO1	S4GO2	S4GO3	S5GO1	S5GO2	S5GO3
TS03	2,01	2,35	2,04	2,70	2,45	2,60	2,03	2,72	3,11	2,12	2,41	2,09	2,67	2,46	2,15
	2,66	2,27	2,42	2,06	1,95	2,61	2,61	2,56	2,25	1,62	2,00	2,21	2,24	2,22	2,05
	2,53	2,18	2,36	1,80	1,67	2,54	2,51	2,83	2,70	2,00	2,10	2,39	3,45	2,37	1,91
	2,42	2,40	2,10	2,36	2,22	2,58	2,30	2,74	2,50	2,09	2,59	2,14	2,37	2,33	1,76
				2,75					2,48	1,99				2,51	
				2,63					2,88	1,97				2,66	
Mean	2,41	2,30	2,23	2,38	2,07	2,58	2,36	2,71	2,65	1,97	2,28	2,21	2,68	2,42	1,97
Median	2,48	2,31	2,23	2,49	2,08	2,59	2,41	2,73	2,60	1,99	2,25	2,18	2,52	2,41	1,98
TS04	2,17	1,15	1,68	2,31	1,68	2,12	1,79	1,85	0,87	2,47	2,46	2,43	2,14	2,47	2,35
	2,09	0,74	2,16	1,61	2,00	2,24	0,99	1,87	2,11	2,04	1,59	2,46	2,41	2,12	2,26
	2,34	1,21	1,78	2,55	2,14	1,95	1,85	1,52	2,06	2,42	1,50	1,93	2,25	1,73	2,68
	2,83	1,36	1,69	2,29	1,99	1,66	0,92	1,97	2,23	2,47	1,62	2,02	2,57	1,83	2,36
		1,52							1,83		2,37				
		2,05							2,17		2,34				
Mean	2,36	1,34	1,83	2,19	1,95	1,99	1,39	1,80	1,88	2,35	1,98	2,21	2,34	2,04	2,41
Median	2,26	1,29	1,73	2,30	2,00	2,04	1,39	1,86	2,09	2,44	1,98	2,22	2,33	1,98	2,35
TS18	1,98	1,68	1,75	1,77	1,79	1,62	1,61	1,36	1,31	1,33	1,48	1,33	1,45	1,35	1,31
	2,50	1,70	1,77	1,82	1,92	1,24	1,59	1,32	1,76	1,36	1,25	1,35	1,44	1,10	1,35
	2,17	1,69	1,85	1,82	1,77	1,50	1,54	1,47	1,75	1,51	1,65	1,37	1,85	1,07	1,38
	2,22	1,72	1,73	1,82	1,99	1,54	1,59	1,42	1,44	1,35	1,52	1,31	1,61	1,27	1,37
			1,60	1,73			1,52	1,50	1,38	1,17	1,69				
			1,61	1,84			1,44	1,31	1,55	1,04	1,75				
Mean	2,22	1,70	1,72	1,80	1,87	1,47	1,55	1,40	1,53	1,30	1,56	1,34	1,59	1,20	1,35
Median	2,19	1,69	1,74	1,82	1,85	1,52	1,56	1,39	1,49	1,34	1,58	1,34	1,53	1,18	1,36
TS21	1,02	1,34	1,85	1,18	2,31	1,99	1,22	1,40	1,54	2,10	2,50	1,81	1,70	1,93	1,62
	0,97	1,55	1,44	1,80	2,58	1,70	1,52	1,33	1,30	3,71	1,98	2,39	2,06	1,85	2,26
	1,21	1,30	1,25	1,71	2,36	1,91	1,34	1,66	1,31	2,97	2,36	1,84	2,00	2,46	2,24
	0,98	1,12	1,37	1,69	2,63	1,63	1,16	1,67	1,51	3,08	2,34	1,33	1,44	2,52	2,26
Mean	1,04	1,33	1,48	1,60	2,47	1,81	1,31	1,51	1,41	2,97	2,30	1,84	1,80	2,19	2,09
Median	1,00	1,32	1,41	1,70	2,47	1,81	1,28	1,53	1,41	3,03	2,35	1,82	1,85	2,20	2,25
TS38	1,86	2,02	2,24	1,81	1,71	2,15	2,43	1,97	2,33	1,89	2,01	2,17	2,59	2,43	2,04
	2,08	2,10	2,37	2,11	1,84	2,29	2,37	2,68	2,06	1,83	2,25	2,70	2,01	2,01	2,31
	1,82	2,16	2,53	2,03	1,79	2,25	2,40	2,28	1,88	1,78	2,15	2,86	2,67	1,52	2,37
	1,89	2,22	2,44	1,95	2,00	2,25	3,02	2,60	2,27	2,17	2,13	2,35	2,76	2,31	2,33
			2,60			1,85				2,16					
			2,56			1,81				1,85					
Mean	1,91	2,13	2,46	1,98	1,83	2,10	2,55	2,39	2,13	1,95	2,14	2,52	2,51	2,07	2,26
Median	1,88	2,13	2,48	1,99	1,82	2,20	2,42	2,44	2,16	1,87	2,14	2,52	2,63	2,16	2,32
TS41	1,81	1,65	2,38	2,01	1,66	2,01	2,22	1,75	2,30	1,05	2,16	1,90	1,31	2,12	1,44
	1,71	1,89	2,55	1,66	1,80	1,31	2,28	1,91	2,08	1,51	1,72	1,83	1,07	1,24	1,42
	1,69	1,82	2,48	1,69	1,74	1,78	2,27	2,22	2,44	1,64	2,21	2,28	1,40	1,61	1,33
	2,18	3,04	2,76	2,01	1,47	1,48	2,35	2,22	2,70	2,47	1,98	2,01	1,24	1,27	1,63
			2,71			1,63			1,84	2,40					
			2,49			1,31			2,04	1,91					
Mean	1,85	2,10	2,56	1,84	1,67	1,59	2,28	2,03	2,23	1,83	2,02	2,01	1,26	1,56	1,45
Median	1,76	1,85	2,52	1,85	1,70	1,55	2,27	2,06	2,19	1,78	2,07	1,96	1,28	1,44	1,43

Table A.6: Short-term Euclidean mimicking results, full.

A.3 The Long-Term Hostile Scenario

Table A.7 shows a complete overview of DTW mimicking results, every WALK included.



	GO1	GO2	GO3	GO4	GO5	GO6	GO7	GO8	GO9	GO10	GO11	GO12	GO13	GO14	GO15
TS01	16,3	13,5	16,21	12,42	12,63	15,47	13,37	13,89	12,56	13,63	13,53	15,5	15,61	14,43	14,24
	11,28	14,66	14,74	13,72	14,96	16,35	10,49	13,71	13,02	12,28	14,12	15,65	15,25	14,24	14,14
				14,31	14,65		12,12	14,41	12,85	13,21	13,25	15,47			
				15,1	13,73		11,91	12,67	14,28	11,56	13,27	16,05			
										14,01					
Mean	13,79	14,08	15,47	13,89	13,99	15,91	11,97	13,67	13,18	12,94	13,55	15,67	15,43	14,34	14,19
Median	13,79	14,08	15,47	14,01	14,19	15,91	12,01	13,8	12,93	13,21	13,4	15,58	15,43	14,34	14,19

	GO16	GO17	GO18	GO19	GO20	GO21	GO22	GO23	GO24	GO25	GO26	GO27	GO28	GO29	GO30
	15,73	14,07	13,64	14,69	14,32	16,19	16,08	15,38	14,72	14,2	16,26	14,22	17,23	12,35	14,42
	14,28	15,06	16,72	14,05	12,82	15,18	15,34	15,8	16,2	17,12	15,62	13,75	14,06	16,77	15,49
						14,59	15,62		15,3	15,16	14,92	13,68			
						15,32	15,12		14,91	15,13	16,21	14,48			
Mean	15,01	14,56	15,18	14,37	13,57	15,32	15,54	15,59	15,28	15,4	15,75	14,03	15,64	14,56	14,96
Median	15,01	14,56	15,18	14,37	13,57	15,25	15,48	15,59	15,1	15,15	15,92	13,98	15,64	14,56	14,96

	GO31	GO32	GO33	GO34	GO35	GO36	GO37	GO38	GO39	GO40	GO41	GO42	GO43	GO44	GO45
	14,03	14,47	13,35	14,36	10,77	11,95	19,66	13,05	12,81	15,62	12,11	18,28	18,65	11,61	13,15
	14,88	14,69	10,84	14,18	11,05	11,55	15,77	14,31	14,02	14,76	11,84	23,28	20,64	11,95	13,57
				12,95	9,836	11,24	20,03	13,51			12,01	19,12			
				10,83	9,812	13,41	16,11	16,41				21,76			
Mean	14,46	14,58	12,1	13,08	10,37	12,04	17,89	14,32	13,41	15,19	11,99	20,61	19,65	11,78	13,36
Median	14,46	14,58	12,1	13,57	10,3	11,75	17,88	13,91	13,41	15,19	12,01	20,44	19,65	11,78	13,36

	GO46	GO47	GO48	GO49	GO50	GO51	GO52	GO53	GO54	GO55	GO56	GO57	GO58	GO59	GO60
	15,13	11,23	13,27	12,37	22,08	14,86	13,95	19,07	14,94	16,77	13,39	22,3	14,13	13,24	14,22
	21,68	11,48	11,46	12,61	12,79	14,84	22,2	21,31	16,75	14,34	12,32	11,4	14,18	14,96	14,22
		10,15				14,22		14,69							
		10,47													
		16,64													
		15,74													
Mean	18,41	12,62	12,37	12,49	17,44	14,64	18,07	18,35	15,85	15,56	12,85	16,85	14,16	14,1	14,22
Median	18,41	11,35	12,37	12,49	17,44	14,84	18,07	19,07	15,85	15,56	12,85	16,85	14,16	14,1	14,22

Table A.7: Long-term DTW mimicking results, full.

Appendix B

Matlab Code

B.1 Signal Preprocessing

The following code performs the preprocessing of gait data. The necessary functions will be included in the following subsections.

```
function [gaitdata, time, resultant] = preprocess(fname)

% readColData is a downloaded function to simplify
% reading from files, it will not be included.
[null,xtime,xdir] =  readColData(fname,4,10,0);

% INTERPOLATE to obtain data table with equal time
% values and corresponding resultant values.
[time,xdir] = interpolate1(xtime,xdir);

% With interpolated values we can remove noise.
% Apply WMA filter and CONVERT to G-forces
[time,dir] = wma(time, xdir);
dir = convert_to_g(dir);

% RESULTANT taking the root of a^2 + b^2 + c^2
resultant = get_resultant(dir);

gaitdata  = zeros(length(resultant),2);

for i = 1:length(resultant)
    gaitdata(i,1) = time(i,1); %Fill with time values
    gaitdata(i,2) = resultant(i,1); %Fill in resultant
end
```

Interpolation

In the following, interp1 is a standard MATLAB function.

```
function [time,dir] = interpolate1(time,dir)

x = transpose(dir(:,1));
y = transpose(dir(:,2));
z = transpose(dir(:,3));

%Arrange observed time values and desired steps
time       = time - time(1,1);
steps      = time(1,1):0.01:time(length(time),1);
ttime      = transpose(time);

ix         = interp1(ttime,x,steps);
iy         = interp1(ttime,y,steps);
iz         = interp1(ttime,z,steps);

xdir = zeros(length(steps),1);
xdir(:,1) = ix(1,:);
xdir(:,2) = iy(1,:);
xdir(:,3) = iz(1,:);
dir = xdir;

time = transpose(steps);
```

WMA Filtering

```
function [time, dir] = wma(xtime, xdir)

dir        = zeros(length(xdir)-4,3);
%WMA for X direction
for i = 3:(length(xdir)-2)
    dir(i-2,1) = (xdir(i-2,1) + 2 * xdir(i-1,1) +
     3 * xdir(i,1,1) + 2 * xdir(i+1,1) +
     xdir(i+2,1)) / 9;
end
```

```
%WMA for Y direction
for i = 3:(length(xdir)-2)
    dir(i-2,2) = (xdir(i-2,2) + 2 * xdir(i-1,2) +
     3 * xdir(i,2) + 2 * xdir(i+1,2) +
     xdir(i+2,2)) / 9;
end
%WMA for Z direction
for i = 3:(length(xdir)-2)
    dir(i-2,3) = (xdir(i-2,3) + 2 * xdir(i-1,3) +
     3 * xdir(i,3) + 2 * xdir(i+1,3) +
     xdir(i+2,3)) / 9;
end

time = zeros(length(xtime)-4,1);
for i=1:length(dir)
    time(i,1) = xtime(i+2,1);
end
```

G-Force Conversion

```
function [gdir] = convert_to_g(xdir)

gdir = zeros(length(xdir),3);
% Constants are specific to the MR100 -1
%device.
XUp   = 591; XDown = 509;
YUp   = 590; YDown = 514;
ZUp   = 576; ZDown = 495;
XStep   = (XUp - XDown) / 2;
YStep   = (YUp - YDown) / 2;
ZStep   = (ZUp - ZDown) / 2;
gdir(:,1) = (xdir(:,1) - (XDown + XStep)) / XStep;
gdir(:,2) = (xdir(:,2) - (YDown + YStep)) / YStep;
gdir(:,3) = (xdir(:,3) - (ZDown + ZStep)) / ZStep;
```

Resultant Calculation

```
function [resultant] = get_resultant(dir)

resultant = zeros(length(dir),1);

for i = 1:length(dir)
    resultant(i,1) = sqrt(dir(i,1)^2 + dir(i,2)^2
    + dir(i,3)^2);
end
```

B.2 Cycle Related Functions

The following functions does work on preprocessed gait data, in order to identify and treat gait cycles. These functions does not depend on distance metrics of any kind, except from omit_cycles where DTW is used. Distance metrics are introduced in the next section.

Cycle Length Estimation

```
function [cyclelength] =
estimate_cyclelength(time,resultant)

%Take _width_ samples from the middle to make subgraph
start_pos    = floor(3*length(time)/4);
stop_pos     = start_pos + (width-1);
subgraph     = resultant(start_pos:stop_pos,1);
min_distance = 80;

%For remembering high correlations
high_correlations = zeros(start_pos,1);
```

```
%Go left to find high correlations, from middle to 1/4
for i = (start_pos - min_distance):-1:
round(length(time)/4)
    tempgraph = resultant(i:(i+length(subgraph)-1));
    correlation = corr(subgraph,tempgraph);
    %Is the correlation above the threshold? Remember
    if correlation >= threshold
        high_correlations(i,1) = correlation;
    end
end

% Find correlation maximums to narrow the vector down to
% starting locations for the subgraph. Peakdet is
% downlaoded code to detect extremas.
[maxtab] = peakdet(transpose(high_correlations),0.001);

%Calculate avg distances. Pairdistance: later in section
cyclelength = pairdistance(transpose(maxtab(:,1)));
```

Cycle Detection

```
function [cycles] = detect_cycles(time,resultant)

% Estimate average length of the cycles
cycle_length = estimate_cyclelength(time,resultant);

% Determine a starting location by looking for a
% minimum in the middle. A window will be checked
% for a maximum, and the search will start from there.
middle      = floor(length(time)/2);
%Buffer to find the middle minimum
startwindow = round(1.2 * cycle_length);
startindex  = 0;
min         = realmax;
```

```
%Determine the minimum and make it the starting point
for i = (middle - startwindow) : (middle + startwindow)
    if (resultant(i,1) < min)
        min = resultant(i,1);
        startindex = i;
    end
end

currentposition = startindex;
minima          = zeros(length(resultant),1);
cyclecounter    = 0;

%FORWARD search
%Check index out of bound
while(currentposition < (length(resultant) - 10))
    %Reset holders
    min       = resultant(currentposition,1);
    minindex  = currentposition;
    %Search current location +- 10 samples
    for i = (currentposition - 10)
     : (currentposition + 10)
        if (resultant(i,1) < min)
            min      = resultant(i,1);
            minindex = i;
        end
    end

    %Minimum now found in a window of 20, minindex
    %pointing to minimum index.
    %Proceed to the next step
    minima(minindex,1)  = min;
    currentposition     = minindex + cycle_length;
    cyclecounter        = cyclecounter + 1;
end
```

```
%BACKWARD search
currentposition         = startindex - cycle_length;
%Check index out of bound
while(currentposition > 10)
    %Reset holders
    min       = resultant(currentposition,1);
    minindex  = currentposition;
    %Search current location +- 10 samples
    for i = (currentposition - 10)
     : (currentposition + 10)
        if (resultant(i,1) < min)
            min      = resultant(i,1);
            minindex = i;
        end
    end

    %Minimum now found in a window of 20, minindex
    %pointing to minimum index
    %Proceed to the next step
    minima(minindex,1)  = min;
    currentposition     = minindex - cycle_length;
    cyclecounter        = cyclecounter + 1;
end

%Done searching, organize findings
cycles = zeros(cyclecounter,2);
pointer = 1;

%Look for non-zero values in minima, store in list
for i = 1:length(minima)
    if(minima(i,1) ˜= 0)
        cycles(pointer,1) = i;
        cycles(pointer,2) = minima(i,1);
        %Point to next free spot in cycle list
        pointer = pointer + 1;
    end
end
```

Cycle Normalization

The following code makes all cycles the same length. Particularly, this code utilizes the *average* cycle length of the subject and makes all cycles adopt this length. If a fixed length is preferred, as for City Block / Manhattan distance - one change to the code is enough: overriding the *avglength* by hard coding to, say, 100 samples. This is noted in the code.

```
function [normalizedcycles] =
normalize_cycles(cycles,resultant)

%Collect cycle characteristics and prepare holders
[avglength, maxlength]
= pairdistance(transpose(cycles));
%pairdistance described later in the appendix
% OVERRIDE IF FIXED LENGTH IS NEEDED
% avglength     = 100;
fullcycles       = zeros(length(cycles)-1,maxlength);
normalizedcycles = zeros(length(cycles)-1,avglength);

%Desired timeline
steps                  = 0.01:0.01:avglength/100;

%Fill fullcycles with all discovered cycles
for i=1:length(cycles)-1
    start           = cycles(i,1);
    stop            = cycles(i+1,1);
    fullcycles(i,1:stop-start)
     = resultant(start:(stop-1),1);
end

%Interpolate cycles
for i = 1:length(cycles)-1
    %Get original length
    oldlength     = cycles(i+1,1) - cycles(i,1);
    %Interpolation neccesary?
    if(oldlength == avglength)
        %Keep original
        normalizedcycles(i,:)
         = fullcycles(i,1:oldlength);
        continue;
    end
    %Skew original steps
    oldsteps = 0.01:(avglength/oldlength)/100:
     avglength/100;
    %Set endpoint
    oldsteps(1,oldlength) = avglength/100;
    %Interpolate based on the skewed old steps
    normalizedcycles(i,:) =
     interp1(oldsteps,fullcycles(i,1:oldlength),steps);
end
```

Omitting Irregular Cycles

```
function [remaining] = omit_cycles(normalizedcycles)

% Gait cycles within the range [avg_dtw +/- threshold
% percentage] will be kept. The threshold is sliding
thresholds    = [0.7, 0.5, 0.3, 0.2];
binarycycles  = ones(1,length(normalizedcycles(:,1)));

% Get DTW matrix for this job (DTW later in appendix)
dtwscores = zeros(length(normalizedcycles(:,1)),
length(normalizedcycles(:,1)));
for i = 1:length(normalizedcycles(:,1))
   for j = i:length(normalizedcycles(:,1))
        dtwscores(i,j) = dtw(normalizedcycles(i,:),
         normalizedcycles(j,:));
   end
end
% Transpose and merge (symmetry)
dtwscores = dtwscores + transpose(dtwscores);

% Perform the reduction of cycles, for each threshold.
for i = 1:length(thresholds(1,:))
    % Calculate mean and reduce degree of freedom by 1
    % because the sum should be divided by n-1
    means = mean(dtwscores,2);
    means = means * length(means) / (length(means) -1);
    totalmean = mean(means);
    %Mark cycles outside acceptable range
    for j = 1:length(means)
        current = means(j,1);
        if((current < (totalmean*(1-thresholds(i))))
         || (current > (totalmean*(1+thresholds(i)))))
            binarycycles(1,j) = 0;
        end
    end

    %Remove irregular cycles
    removed = 0;
    for k = 1:length(binarycycles(1,:))
       if(binarycycles(1,k) == 0)
          normalizedcycles(k-removed,:) = [];
          dtwscores(k-removed,:)        = [];
          dtwscores(:,k-removed)        = [];
          removed                       = removed + 1;
       end
    end
    %Reset binarycycles vector
    binarycycles =
     ones(1,length(normalizedcycles(:,1)));
end

%Holder for remaining cycles (not to be omited)
remainingcycles = normalizedcycles;
```

Cycle Averaging

```
function [meanavg,medianavg]
= average_cycle(normalizedcycles)

%Skip irregular cycles
normalizedcycles = omit_cycles(normalizedcycles);

%Sort every column
normalizedcycles = sort(normalizedcycles);

medianavg = median(normalizedcycles);
meanavg   = mean(normalizedcycles);
```

Cycle Length Helper Function

This function is used by the cycle detection function. In essence, it takes assumed cycle start positions as input, makes sure there is nothing ”wrong” and returns an average cycle length. What can go ”wrong” is that sometimes cycles are NOT detected - if one cycle is ”hidden” between two others, the previous cycle will seem twice as long. This, and similar problems, will be defeated by this function.

```
function [avgdistance,maxlength] = pairdistance(values)

% For total value
sum              = 0;
%For hidden cycles
hidden           = 0;
currently_hidden = 0;

% For determining the max length of a cycle
maxlength        = -realmax;

for i = 1:length(values)-1
    %Find cycle length entries
    temp = (values(1,i+1) - values(1,i));

    %Could there be n cycles hidden in temp?
    for n = 2:10
        if(((temp / n) > 90) && ((temp / n) < 130))
            %n cycles found
            hidden           = hidden + n - 1;
            currently_hidden = n;
            break;
        end
    end
    %If the cycle is even longer or shorter, skip it
    if((temp / 10) > 130 || temp < 80)
        hidden = hidden - 1;
        continue;
    end
    %Add to total
    sum  = sum + temp;
    %Update max. Take hidden cycles into consideration
    if(currently_hidden ~= 0)
        temp = ceil(temp/currently_hidden);
        currently_hidden = 0;
    end
    if(maxlength < temp)
        maxlength = temp;
    end
end

% Calculate the average. If cycles are hidden,
% these must be accounted for.
avgdistance = round(sum/(length(values)-1+hidden));
```

B.3 Template Creation

The following code is applied to create templates, which in essence is an averaged gait cycle for a user. This code is tailored specificly to fit the naming of files and folders during the work.

```
function [] = createtemplates(folder)

%We only want walks
query  = strcat(folder,’/walk*.dat’);
%Fetch walk info
list   = dir(query);
amount = length(list);

%For storing templates
templatefolder = strcat(folder,’’);
```

```
%For all walks found
for i=1:amount
   %Fetch one walk, preprocess and get average cycle
   path               = strcat(folder,’/’,list(i).name);
   [gaitdata, time, resultant]  = preprocess(path);
   cycles             = detect_cycles(time,resultant);
   normalizedcycles   =
    normalize_cycles(cycles,resultant);
   average            = average_cycle(normalizedcycles);

   %Save average as template
   path = strcat(templatefolder,’/t_’,list(i).name);
   save(path,’average’,’-ASCII’);
end
```

B.4 Statistical Distance Determination

The following code is related to statistical distance metrics, such as Dynamic Time Warping (DTW).

Dynamic Time Warping

```
function [dtw_distance] =  dtw(sequenceA,sequenceB)

% Constant costs
c_del = 0.5;
c_ins = 0.5;

%Cost matrix holder
costmatrix = zeros(length(sequenceA) + 1,
length(sequenceB)+1);

%Find maximum set distance (used for c_sub)
S = max(max(sequenceA),max(sequenceB))
- min(min(sequenceA),min(sequenceB));

%Boundary conditions
costmatrix(1,1) = 0.00;
```

```
%First column
for i = 2:length(costmatrix(:,1))
   costmatrix(i,1) = costmatrix(i-1,1) + c_del;
end
%First row
for j = 2:length(costmatrix(1,:))
   costmatrix(1,j) = costmatrix(1,j-1) + c_ins;
end

%The rest of the matrix
for i = 2:length(costmatrix(:,1))
    for j = 2:length(costmatrix(1,:))
       %Fetch value for replacement
       x = sequenceA(1,i-1);
       %Fetch new value
       y = sequenceB(1,j-1);
       %Calculate substitution cost
       c_sub = abs(x - y) / S;
       %Find best path
       costmatrix(i,j) = min([(costmatrix(i-1,j-1)
        + c_sub), (costmatrix(i-1,j) + c_del),
        (costmatrix(i,j-1) + c_ins)]);
    end
end

dtw_distance = costmatrix(end,end);
```

Cycle Shifting for DTW

This function is used to shift the cycle relative to extremas, to obtain correct distance scores even if the cycle is out of sync. This method can be used for ANY distance metrics, by substituting tiny bits of the code, as commented in-line.

```
function [dtw_distance] = dtw_min(sequenceA,sequenceB)

%Determine peaks
maxtabA     = peakdet(sequenceA,0.1);
maxtabB     = peakdet(sequenceB,0.1);
```

```
%Remove peaks that are below threshold
thresholdA  = 0.9*(max(sequenceA)+mean(sequenceA))/2;
thresholdB  = 0.9*(max(sequenceB)+mean(sequenceB))/2;

removed = 0;
for i=1:length(maxtabA(:,1))
    if maxtabA(i-removed,2) < thresholdA
        maxtabA(i-removed,:) = [];
        removed = removed + 1;
    end
end
removed = 0;
for i=1:length(maxtabB(:,1))
    if maxtabB(i-removed,2) < thresholdB
        maxtabB(i-removed,:) = [];
        removed = removed + 1;
    end
end

%Reduce to max four peaks
while(length(maxtabA(:,1)) > 4)
    index = find(maxtabA(:,2) == min(maxtabA(:,2)));
    maxtabA(index,:) = [];
end
while(length(maxtabB(:,1)) > 4)
    index = find(maxtabB(:,2) == min(maxtabB(:,2)));
    maxtabB(index,:) = [];
end

%Shift the sequence with fewest peaks (cosequence)
%The "still" one is the basesequence.
if(length(maxtabA) > length(maxtabB))
    basesequence    = sequenceA;
    cosequence      = sequenceB;
    rotationindex   =
     find(maxtabA(:,2)==max(maxtabA(:,2)));
    rotationpoint   = maxtabA(rotationindex,1);
    cotab           = maxtabB;
```

```
else
    basesequence    = sequenceB;
    cosequence      = sequenceA;
    rotationindex   =
     find(maxtabB(:,2)==max(maxtabB(:,2)));
    rotationpoint   = maxtabB(rotationindex,1);
    cotab           = maxtabA;
end

%Determine rotation point, reachable?
if(rotationpoint > length(cosequence))
    %Shift base sequence and rotation point
    basesequence = circshift(basesequence,[1, -50]);
    rotationpoint = rotationpoint -50;
end

%Begin with the original DTW, and compare
%Can switch to OTHER METRICS here
dtw_mindistance = dtw(sequenceA,sequenceB);

for i = 1:length(cotab(:,1))
    %How many sample indexes to shift
    shift          = rotationpoint - cotab(i,1);
    new_cosequence = circshift(cosequence,[1,shift]);
    %Calculate DTW btw the basesequence and shifted.
    currentDTW = dtw(basesequence,new_cosequence);
    %Update minimum
    if currentDTW < dtw_mindistance
        dtw_mindistance = currentDTW;
    end
end
```

DTW Matrix Calculation

This code produces the average DTW distance matrix in Table A.1 and A.2. This code is tailored specificly to fit the naming of files and folders during the work.

```
function [dtw_pairavg_matrix,dtw_std_matrix,
genuinevector,impostorvector] =
dtw_pairavg(templatefolder_filename,n_persons,skip)

%Holders and settings for DTW
dtw_pairavg_matrix = zeros(n_persons,n_persons);
dtw_std_matrix = zeros(n_persons,n_persons);
% Vectors to be saved for later: genuine and impostor
% comparisons. Can be loaded later to make DET curve.
genuinevector  = [];
impostorvector = [];

%Load all templates into matlab
for i = 1+skip:n_persons
    if i < 10
        templatefolder =
         strcat(templatefolder_filename,’0’,int2str(i));
    else
        templatefolder =
         strcat(templatefolder_filename,int2str(i));
    end
    %We only want templates
    query  = strcat(templatefolder,’/t_*.dat’);
    %Fetch template info
    files   = dir(query);
    namount = length(files);
    %Load
    for j=1:namount
        load(strcat(templatefolder,’/’,files(j).name));
    end
end

%Construct table
for i = 1+skip:n_persons
    %Find person identifier for test subject i
    if (i < 10)
        person_i = strcat(’TS0’,int2str(i));
    else
        person_i = strcat(’TS’,int2str(i));
    end
```

```
%Find average distance from person i to all other
for j = i:n_persons
    %Find person identifier for test subject j
    if (j < 10)
        person_j = strcat(’TS0’,int2str(j));
    else
        person_j = strcat(’TS’,int2str(j));
    end

    %Reset pairdtw
    pairdtw         = zeros(10,10);
    vector          = zeros(1,100);
    %Start comparing walks between person i and j
    for walk_i = 1:10
        %Find walk identifier for person i
        if (walk_i < 10)
            walk_ix = strcat(’0’,int2str(walk_i));
        else
            walk_ix = int2str(walk_i);
        end
        for walk_j = 1:10
            %Find walk identifier for person j
            if (walk_j < 10)
                walk_jx =
                 strcat(’0’,int2str(walk_j));
            else
                walk_jx = int2str(walk_j);
            end
            %Calculate DTW OR OTHER METRIC
            pairdtw(walk_i,walk_j) =
             dtw_min(eval(strcat(’t_walk’,
             walk_ix,’_’,person_i)), eval(strcat(
             ’t_walk’,walk_jx,’_’,person_j)));
        end
    end
    %Find the grand mean/std between person i and j
    vector(1,:)             = pairdtw(:);
    dtw_pairavg_matrix(i,j) = mean(vector);
    dtw_std_matrix(i,j)     = std(vector);
```

```
        %Also update genuine / impostorvector
        if(j==i)
            genuinevector = [genuinevector,vector];
        else
            impostorvector = [impostorvector,vector];
        end
    end
end
```

DTW Attack Script

This function was used for attack scripting during the hostile experiment scenarios. This code is tailored specificly to fit the naming of files and folders during the work. Any distance metric may be used by changing tiny pieces of the code, as commented in-line.

```
function [attack_dtwmatrix, a_cyclelengths,
v_cyclelengths] = dtw_attack(
victimfolder, attackfolder)

%Get victim data
vquery  = strcat(victimfolder,’/t_⋆.dat’);
vfiles   = dir(vquery);
vamount = length(vfiles);

%Get attacker data
vquery  = strcat(attackfolder,’/t_⋆.dat’);
afiles   = dir(vquery);
aamount = length(afiles);

%Holders and settings for DTW, and cyclelengths
attack_dtwmatrix = zeros(aamount,vamount);
a_cyclelengths = zeros(aamount,1);
v_cyclelengths = zeros(vamount,1);

%Load all templates found to matlab
for i=1:vamount
   load(strcat(victimfolder,’/’,vfiles(i).name));
   v_cyclelengths(i,1) =
    length(eval(vfiles(i).name(1,1:end-4)));
end
```

```
for i=1:aamount
   load(strcat(attackfolder,’/’,afiles(i).name));
   a_cyclelengths(i,1) =
    length(eval(afiles(i).name(1,1:end-4)));
end

%Calculate DTW matrix. Other metric possible!
%Row loop
for i = 1:aamount
    %Column loop
    for j = 1:vamount
        %Calculate DTW (or switch to other metric)
        attack_dtwmatrix(i,j) =
         dtw_min(eval(afiles(i).name(1,1:end-4)),
         eval(vfiles(j).name(1,1:end-4)));
    end
end
```

Euclidean Distance

This code may substitute any use of the DTW metric.

```
function [euclid_distance] = euclid(sequenceA,sequenceB)

sum = 0;
for i=1:length(sequenceA)
    sum = sum+abs((sequenceA(1,i)-sequenceB(1,i)))^2;
end
euclid_distance = sqrt(sum);
```

Manhattan / City Block Distance

This code may substitute any use of the DTW metric.

```
function [cb_distance] = cb(sequenceA,sequenceB)

cb_distance = 0;
for i=1:length(sequenceA)
    cb_distance = cb_distance
      + abs((sequenceA(1,i)-sequenceB(1,i)));
end
```

B.5 Creation of DET Curves

```
function [fmr,fnmr,EER]
= CreateDET(genuine,impostor)

%Find minimums and maximums
minima = min(min(genuine),min(impostor));
maxima = max(max(genuine),max(impostor));

%Holders
fmr=[];
fnmr=[];

global thresholds;
thresholds=sort([genuine,impostor]);

%Try for different tresholds
for i=1:(length(thresholds))
    t=thresholds(i);
    fmr=[fmr,sum(impostor<=t)];
    fnmr=[fnmr,sum(genuine>t)];
end
fmr=fmr/length(impostor);
fnmr=fnmr/length(genuine);
```

```
%Find EER
i=1;
while (fmr(i)<fnmr(i))
    i=i+1;
end

i=i-1;

if (fmr(i)==fnmr(i))
    EER=fmr(i);
else
    EER=(fmr(i)+fmr(i+1)+fnmr(i)+fnmr(i+1))/4;
end

x=0:0.1:1;
plot(fmr,fnmr’black’,x,x,’black’);
```

B.6 Usage Examples

This code is tailored specificly to fit the naming of files and folders during the work.

To look at specific WALKS and do some plotting, the following can be used. In this example *walk01_TS01.dat* is a raw data file, containing one WALK only.

```
[gaitdata, time, resultant] =
preprocess(’TSfix/TS01/walk01_TS01.dat’);
cycles = detect_cycles(time,resultant);
normalizedcycles =
normalize_cycles_fixed(cycles,resultant);
remainingcycles = omit_cycles(normalizedcycles);
plot(1:length(remainingcycles),remainingcycles);
```

An attack, where *VTS16* and *TS01* are the victim and attacker folders, respectively:

```
[distances attacker_cyclelengths
victim_cyclelength] = dtw_attack(
’VTS16’,TS01’);
```

Calculating statistical data (see Chapter 7).

```
%Regression model
function [F] = funexp(a,data)
F=a(1) + a(2)*exp(a(3)./data);

% Assuming vector gaitdata with filtered observations,
% and vector beta0 with initial guess of regression
% parameters (e.g. [5 1 1], found by trial and error).
X1 = 1:length(gaitdata);

% Estimate new beta values, residuals r, Jacobian J,
% covariance matrix COVB, and MSE
[beta,r,J,COVB,mse] =
nlinfit(X1,gaitdata,@funexp,beta0);

% Construct regression line and plot
F = funexp(beta,X1);
plot(X1,gaitdata,’black’,X1,F,’black’)

% Confidence intervals
ci = nlparci(beta,r,’covar’,COVB);

%Perform regression on residuals
stats = regstats(r,X1,’linear’);

% Access residual statistical data by stats.beta,
% stats.t.pval (pvalue for parameter significance),
% stats.mse etc.
```

B.7 Disclaimer

All code files contain a disclaimer, here is an example:

```
% Description:
% This function computes intra-person DTW matrix
% for every person against eachother in terms of
% average DTW distance. Hence, d(i,j) in this matrix
% will be the average distance between person i and j.
% Also, the method returns the DTW comparisons in
% terms of a genuine and impostor vector, which can
% be used to calculate a DET curve later.
%
% Input:
% templatefolder_filename - root folder as input,
% including the beginning of the subfolders for
% each user, such as ’TS/TS’ where TSxx are the
% subfolders, so person 6 is ’TS/TS06’.
% n_persons - how many persons to process
% skip - how many persons to skip (e.g. skip = 10
% will result in all persons in the interval
% <skip,n_persons] to be processed.
%
% Output:
% dtw_pairavg_matrix - a matrix where cell (i,j)
% represents the DTW distance between person i/j.
% dtw_std_matrix - i/j standard deviation
% genuinevector - all genuine comparisons
% impostorvector - all fraudulent comparisons
%
% Author:
% Bendik B. Mjaaland, 2009
% Norwegian University of Science and Technology (NTNU)
%
% Disclaimer:
% This piece of software is not copyrighted,
% and anyone are free to use it in any context
% as long as the author information and
% this disclaimer is preserved.
```

Appendix C

Miscellaneous

C.1 Raw Data Example

Here is an example extraction from a raw data file provided by the MR100 sensor. The first column are time values, while the following three columns represent acceleration (not g-values) in the X, Y and Z direction, respectively. Figure C.1 shows the graph of the total gait sequence.

```
<<< BEGIN HEADER >>>           <<< END HEADER >>>
Start time: 12/02/2009-15:47  43.297085 520 471 536
Stop time:  12/02/2009-15:48  43.307110 518 471 532
Sample interval: 0.017579     43.317177 517 470 539
Sample count: 11938           43.327251 515 467 535
Raw data file: 120220091..    43.337318 518 468 542
Sensor type: MR100 Sensor     43.347385 517 469 535
Sensor ID: 1005               43.357452 515 469 536
MR Analyser version: 3..      43.367523 517 471 539
```

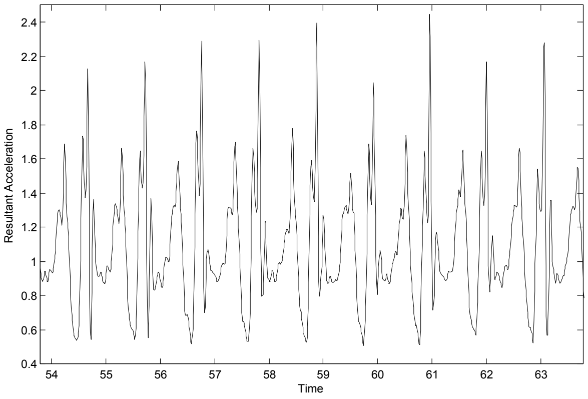
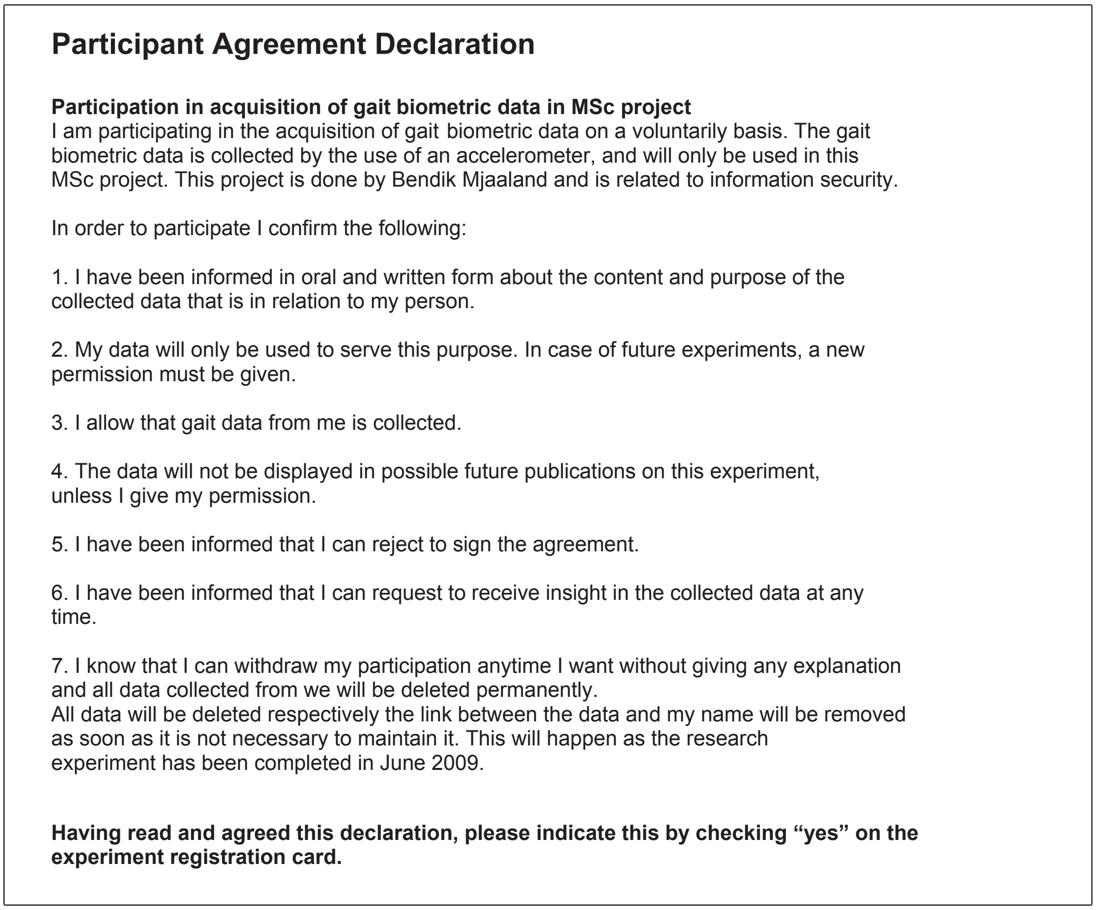


Figure C.1: Raw data plot.

C.2 Participant Agreement Declaration



Participant Agreement Declaration

Participation in acquisition of gait biometric data in MSc project
I am participating in the acquisition of gait biometric data on a voluntarily basis. The gait biometric data is collected by the use of an accelerometer, and will only be used in this MSc project. This project is done by Bendik Mjaaland and is related to information security.

In order to participate 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. In case of future experiments, a new permission must be given.

3. I allow that gait data from me is collected.

4. The data will not be displayed in possible future publications on this experiment, unless I give my permission.

5. I have been informed that I can reject to sign the agreement.

6. I have been informed that I can request to receive insight in the collected data at any time.

7. 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 removed as soon as it is not necessary to maintain it. This will happen as the research experiment has been completed in June 2009.

Having read and agreed this declaration, please indicate this by checking “yes” on the experiment registration card.

C.3 Participant Registration Form

All participants filled in the following:

- Name
- Gender
- Age
- Height
- Weight
- Hip-knee distance (unused)
- Knee-ankle distance (unused)
- Shoe characteristics
- E-mail
- Phone number
- Injuries or other handicaps
- Willingness to participate in the hostile scenario
- Agreement to the PAD (previous section)

This data was stored in a different location than the actual biometric data. This way, following Norwegian law, no database of biometric data was ever generated during the thesis work. All data was disposed of after the thesis, unless specific agreements were made with the participants.