Bours, P. & Shrestha, R. (2010). Eigensteps: A giant leap for gait recognition. I: *2nd International Workshop on Security and Communication Networks (IWSCN), 2010*, IEEE conference proceedings.

Internet address:
doi: 10.1109/IWSCN.2010.5497991

Eigensteps: A giant leap for gait recognition

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***Abstract*—In this paper we will show that using Principle Component Analysis (PCA) on accelerometer based gait data will give a large improvement on the performance. On a dataset of 720 gait samples (60 volunteers and 12 gait samples per volunteer) we achieved an EER of 1.6% while the best result so far, using the Average Cycle Method (ACM), gave a result of nearly 6%. This tremendous increase makes gait recognition a viable method in commercial applications in the near future.**

I. INTRODUCTION

In our current society we need to prove our identity in many different places. Using passports to cross borders, using a password to get access to a computer, using a PIN code to open our mobile phones, or in combination with a banking card to get money from our account. Passwords and PIN codes have the obvious disadvantage that we need to remember many of them and we either tend to forget them, write them down, or choose simple ones. This works against having a strong mechanism for access control. What we in general do want is an authentication method that we cannot forget or loose (either physically or from our memory) and is still easy to use. Biometrics is such a method and fingerprint and face recognition are already often used and well excepted authentication methods. In many cases however, we do not just want an easy to use authentication method, but even one that works without any interference or action from our side. In such a case we do often need to turn to behavioural biometrics and gait recognition is such a method. Gait, the way we walk, can be captured and processed unobtrusively and can therefore play a future role as an authentication method. So far the performance results on gait recognition have not been such that it allows for large scale commercial deployment, but in this paper we will describe an analysis method where we can make a giant leap towards commercial use. The techniques we used are not new as such; Principle Component Analysis has been used before in for example face recognition [1], and also wearable sensor based gait recognition is not new [2], [3]. However, this is the firs paper in which these techniques have been combined, giving very good results.

In the future we could imagine protecting our mobile devices (e.g. PDA and phones) using our own gait. The new mobile devices already contain accelerometers and we could use the output of these accelerometers to recognize the owner of the device. Modern mobile phones are no longer just used for making phone calls or sending text messages, but they are often synchronized with email accounts, contain sensitive documents or store sensitive information for m-banking. The current protection mechanism on a mobile phone is a PIN code, that only needs to be entered when the phone is turned on. The number of people that use a PIN code to activate a phone that has gone to stand-by mode is extremely low, mostly because the extra effort of typing a PIN code whenever the phone is needed is seen as a burden. Using gait recognition to keep track if the phone is still in the possession of its genuine owner can be an add-on that can provide extra, effortless security. Such a phone would lock itself if it detects that the current way of walking does not fi with the walking of its owner. In case of a false negative, the user needs to unlock the phone with the PIN code, but given the performance of gait recognition reported in this paper, it is likely to happen only very infrequently, and thus is it a small price to pay for the increased security.

The remainder of the paper is organized as follows. In Section II we will briefl describe current techniques used in gait recognition biometrics. Sections III and IV we will describe the basics of the Average Cycle Method (ACM) and of Principle Component Analysis (PCA). Section V will start with a description of the used database and will then describe how the data is pre-processed and analyzed. Finally Sections VI and VII will give the results of the analysis on the used dataset and will draw conclusion on the results given in this paper.

II. GAIT RECOGNITION

Within gait recognition we try to recognize a person by the way he or she is walking. This can be either in an identificatio setting, used for example in surveillance, or in an authentication setting, which can for example be applied in securing access to mobile devices. There exist 3 major approaches to gait recognition. The firs and most used one is called Machine Vision (MV) based gait recognition. In this case the walking behaviour is captured on video and video processing techniques are used for analysis. The second technique is called Floor Sensor (FS) based gait recognition. In this case sensors are placed in the floo that can measure force and use this information for analysis. Such a system can for example be used for controlling access into a building. Both MV and FS based gait recognition are well suited for identificatio purposes.

The fina method is referred to as Wearable Sensor (WS) based gait recognition. In this case the user wears a device

Fig. 1. MR100 Sensor used in the experiment [5]

that measures the way of walking and pattern recognition techniques can now be used for recognition purposes. WS based gait recognition is very well suited for authentication purposes. In our case the wearable sensor (as shown in Figure 1) is an MR100 accelerometer [4], which measures acceleration in 3 perpendicular directions (referred to as x, y, and z). The MR100 measures and stores approximately 100 data points per second for each of the 3 directions.

Accelerometer based gait recognition has first been explored in 2005 [2], [3]. Approaches in WS based gait recognition often use a variation of the Average Cycle Method [6], which is explain in more detail in Section III. In the ACM method the collected gait data is represented by an ”average cycle” which is then used for comparisons in the analysis. Some of the reports are on performance of gait authentication [7], while others focus on security issues like how easy it is to copy the gait characteristics of another person [8]. Also issues related to different walking circumstances have been investigated before [5].

In this article we will focus on the use of Principle Component Analysis (PCA) in gait recognition as an additional step in the Average Cycle Method. PCA will be discussed in more detail in Section IV. PCA has been applied in other biometric research before, in particular in face recognition [1]. It has also been used before in gait recognition, in particular in MV based gait recognition, for example in [9]–[14]. In [15] the authors actually apply PCA to a Floor Sensor system, but the goal in that article is to discriminate between normal and abnormal walking and not so much user identification or authentication.

To our best knowledge PCA has never been applied to accelerometer based gait recognition. The only time PCA was used with accelerometer based gait data was to distinguish abnormal walking behaviour [16], [17], similar to what was done in [15].

III. Average Cycle Method (ACM)

The main idea behind the Average Cycle Method [5], [6] is to represent a full gait sample (as can be seen in Figure 2 by a single gait cycle, where this single cycle in some way or another represents the average cycle present in the full gait sample. The ACM consists of various steps: (1) preprocessing; (2) cycle detection; (3) creating the average cycle; and (4) performance analysis. These steps are explained below in more detail.

(1) The preprocessing of the data depends heavily on the used sensor. One of the actions taken in this step will be the reduction of noise in the collected data, for example by using a Moving Average or Weighted Moving Average filter [5], but different types of filters can also be applied [7]. In case of the MR100 sensor we also performed time equalization between the data points in a gait sample in this step, because the time between two data points was not constant.

(2) The most important step is the ACM is obviously the detection of single cycles in the data signal. Different methods for this are used by Gafurov et al. [6], Holien [5] and Derawi et al. [18]. The first action in this step is to determine approximately how many data points one cycle contains. Let N_{approx} denote this estimated value. The common basic idea in cycle detection is that given the start of a cycle we can find the start of the next cycle (and hence the ending of the current cycle) by looking approximately N_{approx} data points further in the gait sample. In Figure 2 we can see a gait sample and how that sample is split into distinct cycles, where the start and end of a cycle is denoted by a circle.

(3) For creating the average cycle again different techniques can be used, and the chosen technique depends partly also on the distance metric that is used in step (4). Often the separate cycles are first ”normalized” to have 100 data points per cycle by using linear interpolation [6]. In such a case the average cycle can be calculated by simply using the mean or median per each of the 100 data points over the detected cycles. Another way of finding an average cycle is by selecting the cycle that has the least average Dynamic Time Warping (DTW) distance to the other detected cycles [5]. We do not need to normalize the cycles to a fixed number of data points in order to apply DTW averaging, although DTW can still be applied if the cycles are normalized.

(4) During the performance analysis we compare the average cycles to each other. Different distance metrics can be applied in this case, for example Euclidean distance, Manhattan distance and DTW distance (otherwise also know as edit distance or Levenshtein distance). In case of Euclidean and Manhattan distance it is needed that all cycles have the same number of data points, but such a restriction does not apply for the DTW distance [5].

IV. Principle Component Analysis (PCA)

Principle Component Analysis is a statistical technique that is not unknown in the field of biometrics. It has been mainly

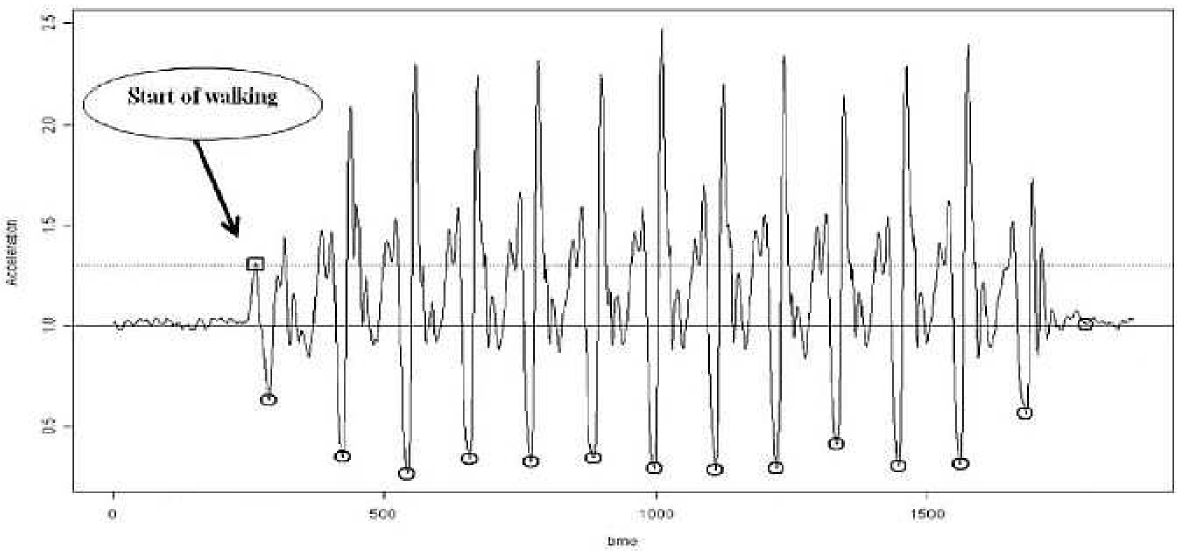

Fig. 2. A gait data sample showing detected cycles [19].

applied to face recognition before, but also to MV based gait recognition. To our best knowledge it has never been used on WS based gait recognition before. In general any multi-dimensional source of information is expressed in the basis consisting of the unit-vectors $\vec{e_i}$. For example any point $\vec{p} = (x, y, z) \in \mathbb{R}^3$ can be expressed as $\vec{p} = x \cdot \vec{e_1} + y \cdot \vec{e_2} + z \cdot \vec{e_3}$. We can use any other basis $\{\vec{b_1}, \vec{b_2}, \vec{b_3}\}$ and express $\vec{p}$ as $\vec{p} = x' \cdot \vec{b_1} + y' \cdot \vec{b_2} + z' \cdot \vec{b_3}$ for particular values x', y', and z'.

The idea behind PCA [20] is to find new basis vectors that express the underlying dataset best. Given a dataset, PCA will find new basis vectors such that the first basis vector will contain the most information about the underlying dataset. The next basis vector will contain a little less information, and in fact each following basis vector will contain less information about the dataset as the basis vectors before. The basis vectors are also called eigenvectors and the importance of the basis vectors is expressed in the so called eigenvalues. The number of eigenvalues equals the number of eigenvectors, which is again equal to the number of dimensions in the dataset.

When performing PCA analysis in (gait) biometrics, we need to split up our dataset in three parts. The first part will be used to "train" the PCA, i.e. to find the eigenvectors. Analogue to face recognition, where the eigenvectors are called eigenfaces, will we name the eigenvectors eigensteps, as they are based upon an underlying dataset of single steps. The second part will be used to create templates for each user. Finally the third part will be used for testing, i.e. comparing against the templates.

V. Experiment design and data analysis

In this section we will first describe the design of our experiment. Next we will discuss how the collected acceleration data is preprocessed and analyzed.

A. *Experiment design*

In the experiment we used 60 volunteers, 43 of which were male and 17 were female. The average age of the male volunteers was 32.9 year with a standard deviation of 11.04 year. For the female volunteers the average age was 35.1 year with a standard deviation of 15.24 year. All volunteers participated in 2 sessions. In both of these sessions the volunteers provided 6 gait samples. This makes a total of $2 \cdot 6 = 12$ gait samples per user and $60 \cdot 12 = 720$ gait samples in total.

The environment where the experiment took place was a large room, about 20 meters long and the floor was flat. The participants were asked to walk in a normal way, at their own normal speed, in a straight line from one end of the room to the other. Each such walk would provide one gait sample, hence to collect the 6 gait samples for each of the sessions, the volunteers had to walk up and down the room 6 times (3 times up and 3 times down). Before the volunteers started walking, the MR100 sensor (see Figure 1) containing the 3 perpendicular accelerometers was attached to the left hip of the volunteers. The MR100 sensor was attached every time in a more or less fixed position, with obviously some small deviations for every time it was attached. We made sure that during both sessions the volunteers wore the same (type of) shoe, such that the influence on the gait due to the shoe ware would be minimal. The accelerometer data was collected inside the MR100 sensor and was downloaded after each session to a computer. The data was stored in file in such a way that the volunteer and the session could be identified from the filename.

After the experiment we had 120 files, where for each volunteer we had 2 files, and each file contained the data of 1 session. Each file was split into 6 new files, where each new file contained one of the gait samples related to walking the full distance of the room once, hence each new file corresponded to exactly one gait sample. The filename of the resulting $6 \cdot 120 = 720$ files identified the volunteer, the session and the gait sample within that session. The information contained in each of these 720 files are 4 columns with data. The first column was a timestamp, and the second till the forth column represented the x-, y- and z-acceleration measured at the particular timestamp. The MR100 sensor collected the accelerometer values at approximately (but not exactly) 100 data points per second. In particular, the difference between two timestamps was not always the same and not always equal to 10 milliseconds.

B. Data preprocessing and analysis

For the data processing we followed to a large extent the Average Cycle Method (ACM) as it was described in [6] with variations described in [5] and in [18]. We then also included our own addition of the PCA. As described in Section III is the ACM a method in which various algorithms can be plugged in, for example the filtering of the data to reduce the noise can be done using the Moving Average (MA) filter, as was done in [6] or the Weighted Moving Average (WMA) filter as is done in [5]. The major differences between [18], [6], and [5] lies in the cycle detection. The cycle detection in [6] is relatively simple but still functions very well. This was the basis for the cycle detection in [5] which was rather elaborative but performed also much better. On the dataset we are using, the cycle detection method from Gafurov [6] results in an EER of 25%, using Euclidean metric as a distance metric. Under the same circumstances, only replacing Gafurov's cycle detection method by the one from Holien [5], the EER drops down to 8.4%. Actually Holien's best result on this dataset is when using Dynamic Time Warping (DTW) as a distance metric, giving an EER of 5.9%. Derawi's cycle detection method is again derived from Holien's, but simplified and actually the best result is an EER of 5.7% with the Cyclic Rotation Method (CRM) as the distance metric [18].

In our analysis we actually used all three above mentioned cycle detection methods. We will show that when combining the ACM with PCA all three methods perform more or less the same. This indicates that using the simple method from [6] may already be good enough when combining PCA with ACM. In the remaining description we will assume that a general cycle detection method is used because the particular used method is not important for the description. As a first analysis step the gait data is preprocessed and each of the 720 gait samples is split into separate cycles, after which each of the cycles is then normalized to 100 values using linear interpolation. This corresponds to steps (1) and (2) of the ACM (see Section III).

As mentioned in Section IV, we need to split the dataset into three parts. We used 2 gait samples per person for training the PCA, 1 to create the template and the remaining 9 to test the performance. In order to calculate the eigensteps we use 2 gait samples per participant and from each of these 60*2 gait samples all the cycles are used. The total number N_{cycles} of

	Gafurov [6]	Holien [5]	Derawi [18]
N_{cycles}	1275	1566	1498
N_λ	17	16	17

TABLE I
NUMBER OF DETECTED CYCLES WHEN APPLYING VARIOUS CYCLE DETECTION METHODS.

cycles in all of the gait samples is highly dependent on the used cycle detection method and these values are given in Table I. As was to be expected, the most complicated cycle detection method by Holien [5] detected the most cycles within this set of 120 gait samples. The less complicated method by Gafurov et al. [6] detected the least number of cycles.

Each of the cycles was normalized using linear interpolation to contain exactly 100 values. We denote these cycles by $\vec{c_i}$ for $i = 1, \ldots, N_{cycles}$ and $\vec{c}_{average}$ denotes the average of these cycles. PCA is applied to the vectors $\vec{c_i'} = \vec{c_i} - \vec{c}_{average}$, and the resulting eigensteps are denoted by $\vec{p_i}$ with corresponding eigenvalues λ_i, where $i = 1, \ldots, 100$.

We can now express cycles $\vec{s}$ and $\vec{t}$ in terms of these eigensteps, i.e.:

$$\vec{s} = \vec{c}_{average} + \alpha_1 \cdot \vec{p_1} + \alpha_2 \cdot \vec{p_2} + \cdots + \alpha_{100} \cdot \vec{p_{100}},$$

and

$$\vec{t} = \vec{c}_{average} + \beta_1 \cdot \vec{p_1} + \beta_2 \cdot \vec{p_2} + \cdots + \beta_{100} \cdot \vec{p_{100}}.$$

The distance between $\vec{s}$ and $\vec{t}$ can now simply be expressed in terms of Manhattan or Euclidean distance, either weighted with the eigenvalues or not. For example, the Weighted Euclidean (WE) and Euclidean (E) distance between $\vec{s}$ and $\vec{t}$ can be expressed as:

$$d_{WE}(\vec{s}, \vec{t}) = \sum_{i=1}^{100} \lambda_i \cdot (\alpha_i - \beta_i)^2; \quad (1)$$

$$d_E(\vec{s}, \vec{t}) = \sum_{i=1}^{100} (\alpha_i - \beta_i)^2. \quad (2)$$

Similarly can we express the Weighted Manhattan (WM) and Manhattan (M) distance between these input values as:

$$d_{WM}(\vec{s}, \vec{t}) = \sum_{i=1}^{100} \lambda_i \cdot |\alpha_i - \beta_i|; \quad (3)$$

$$d_M(\vec{s}, \vec{t}) = \sum_{i=1}^{100} |\alpha_i - \beta_i|. \quad (4)$$

As the values of λ_i rapidly become smaller and smaller, we do not need the full summation from $i = 1$ to 100, but we can stop earlier. The eigenvalues are normalized, by dividing each original eigenvalue by the sum of all original eigenvalues. In this way we know that the sum of the normalized eigenvalues equals 1. Now the number N_λ of indices that is used in the summations (1)-(4) is determined as the minimal value such that

$$\sum_{i=1}^{N_\lambda} \lambda_i \geq 0.95,$$

	Gafurov [6]	Holien [5]	Derawi [18]
M	1.6808	1.6682	1.6777
WM	1.6808	1.6667	1.6620
E	1.6808	1.6682	1.6667
WE	1.6808	1.6667	1.6400

TABLE II
EER WHEN COMBINING PCA AND ACM ACCORDING TO VARIOUS CYCLE DETECTION METHODS.

	Gafurov [6]	Holien [5]	Derawi [18]
E	25	8.4	8.2
DTW	11.75	5.9	7.4
CRM	-	-	5.7

TABLE III
EER OF APPLYING VARIOUS DISTANCE METRICS TO THE DATASET SPLIT ACCORDING TO VARIOUS CYCLE DETECTION METHODS.

where λ_i represents the normalized eigenvalues. Obviously the values of N_λ depend again on the used cycle detection method and are given in Table I.

For each of the remaining 10 gait samples per participant we calculated the average cycles per gait sample, exactly like in the ACM. We used the mean to create the average cycle from the separate cycles in a gait sample. From these 10 average cycles per person, 1 was used as a template, while the other 9 were used for testing. All of the average cycles were expressed in their eigenstep coordinates. In this way we have 60 templates and 540 test vectors. When comparing all templates against all test vectors, we found $60 \cdot 9 = 540$ genuine attempts and $60 \cdot 59 \cdot 9 = 31.860$ impostor attempts.

The four distance metrics in equations (1)-(4) were applied, where the summation was from 1 to N_λ instead of 1 to 100. Per applied distance metric we found 540 genuine and 31.860 impostor scores, and from these values we determine the False Match Rates (FMR) and False Non-Match Rates (FNMR). From the FMR and FNMR, the Equal Error Rate (EER) was determined.

VI. RESULTS

In this section we will present the results of our research. As described in Section V-B we used three different cycle detection methods. Each of the 3 cycle detection methods is combined with the distance metrics described in equations (1)-(4). In Table II all the resulting EER values are displayed. In this table, the columns represent the 3 used cycle detection methods, while the rows represent the 4 used distance metrics: Manhattan (M), Weighted Manhattan (WM), Euclidean (E) and Weighted Euclidean (WE).

For comparison reasons we represent in Table III the best known EER results on the used database given the analysis methods from [5], [6], and [18]. We did apply 3 different distance metrics in this case: Euclidean (E), Dynamic Time Warping (DTW) and Cyclic Rotation Method (CRM). As the CRM distance metric is new from [18], we do not have results on how well it performs when the cycle detection method from [6] or from [5] is used.

From Table II we can see that the performances for each of the cycle detection methods are more or less all around 1.6-1.7% EER. This means that for the PCA analysis it is not that important what cycle detection method is used. We also clearly see from the results in Tables II and III that our method by far outperformes the known methods. We see that the best performance is by Derawi et.al., giving a 5.7% EER, using an advanced distance metric called Cyclic Rotation Method [18]. We get down to a 1.64% EER, which is almost 3.5 times as low, using the 'simple' weighted Euclidean distance metric. The best results for the Euclidean distance with the previous methods was 8.2% when using the cycle detection method by Derawi et al. [18], which is almost 5 times as high as the best result we obtain with the Euclidean distance.

VII. CONCLUSIONS

From face recognition we already know that PCA is a technique that can give good recognition rates. PCA has also been applied to Machine Vision based gait recognition before, but never to Wearable Sensor based gait recognition. Using the relatively simple cycle detection from [6] we already got an EER of 1.68%. This is an improvement by approximately a factor of 3.5 compared to the best known results on this database and an improvement of a factor 15 for comparable preprocessing. Possibly we will even get further improvements in performance by having a closer study of different distance metrics.

The merit of these results is not only the improvement of the gait recognition performance, but this can also be seen as a f rst step to a combination of recognizing not only that a person is walking (as opposed to for example sitting, running, cycling, etc.) but also who the person is (either identifying or authenticating that person). Particularly the recognition of the walking activity is very important in a real implementation of a gait recognition system. Such a system should not give false alarms if the owner is not walking. In particular, the system (e.g. implemented in a mobile phone) f rst needs to recognize the particular activity (walking in our case) and can then in the second stage recognize if the walking is indeed from the expected user. This will be future research.

VIII. ACKNOWLEDGMENTS

The authors would like to thank all the (anonymous) participants in this experiment. The writing of this article would not have been possible without their effort in the data collection phase. We also want to express our gratitude to Mohammad Derawi who implemented the three cycles detection methods from [3], [5], [18] and provided us with the resulting sample data split into separate cycles. Finally we would also kindly like to thank Motion Recording for allowing us to use their hardware and download software.

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