Redaktør: Patrick Bours, Norwegian Information Security Laboratory (NISlab),
Gjøvik University College

Norwegian Information Security Conference
Norsk Informasjonssikkerhetskonferanse
NISK 2010

Gjøvik University College, Gjøvik
23.–24. november 2010

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Preface

Welcome to NISK 2010, the third edition of the Norwegian Information Security Conference. After the initial NISK conference in Agder and its follow up in Trondheim, it will now take place in Gjøvik on the 23^{rd} and 24^{th} of November. As before the conference will take place in combination with NIK and NOKOBIT. NISK2010 is sponsored by NISnet, the resource network of Norwegian Information Security researchers funded by the Norwegian Research Council.

This year we had 27 high quality submissions from 8 different institutes. Of those one was withdrawn and one came in too late. The remaining 25 were reviewed by 2 members of the Program Committee each and from their feedback 14 papers were selected for presentation. This means that the acceptance rate of 56% is very close the the 58% from last year. All 14 papers will get a 30 minutes timeslot for presenting the ideas. Out of the 14 papers, 8 are authored or co-authored by PhD students and 1 is co-authored by master students.

We are glad to announce that Dr. Mike Bond from the Computer Laboratory at the University of Cambridge accepted the invitation as a keynote speaker. The title of his presentation is *Chip and Empiricism: Breaking EMV, with proof.* In May 2010 Mike Bond presented the controversial paper *Chip and PIN is broken*, which he co-authored with Steven J. Murdoch, Saar Drimer, and Ross Anderson, at USENIX Security. The paper described how an EMV card can be used to make purchases at Point-of-Sale without knowing the correct PIN. During the subsequent publicity, demonstrations of the technique deployed against the live banking system aired on various European television channels.

I would like to thank all the members of the Program Committee for their valuable input in the reviewing process. Furthermore I would like to thank the organizers of NIK, Erik Hjelmås and of NOKOBIT, Tom Røise for the pleasant cooperation and last but certainly not least I would like to thank Kari Lauritzen for all the help with the practical organization of the three conferences.

Table of Content

NISK 2010

Accelerometer-Based Gait Analysis, A survey

Mohammad Omar Derawi
Norwegian Information Security Lab.
Gjøvik University College, Norway
mohammad.derawi@hig.no

Abstract

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

1 Introduction

A particular way or manner of moving on foot is the definition for gait. Every person has his or her own way of walking. Several human factors, such as aging, injuries, operations on the foot etc. may change a person's walking style into a slight different walk, either permanent or temporary. Elders have a reduced range of hip motion at faster walking speeds and 5 degrees less hip extension than in their in younger age [1]. It also appears from early medical studies that there are twenty-four different components to human gait, and that if all the measurements are considered, gait is unique [2]. This has made gait recognition an interesting topic to be used for identifying individuals by the manner in which they walk. Furthermore, Figure 1 illustrates the complex biological process of the musculo-skeletal system, which can be divided into numerous types of sub events of human-gait. The instances that are shown in that figure are used to extract parameters for being used as an identification system of each individual.

The analysis of biometric gait recognition has been studied for a longer period of time [4, 5, 6, 7, 8] for the use in identification, surveillance and forensic systems and is becoming important, since they provide more reliable and efficient means of identity verification.

There are three different approaches in gait recognition; *Machine Vision Based (MV)*, *Floor Sensor based (FS)* and *Wearable Sensor based (WS)*. In the machine vision approach, the system will typical consist of several digital or analog cameras (black-and-white or color) with suitable optics for acquiring the gait data. Using techniques such as thresholding which converts images into simply black and white; pixel counting to count

This paper was presented at the NISK-2010 conference.

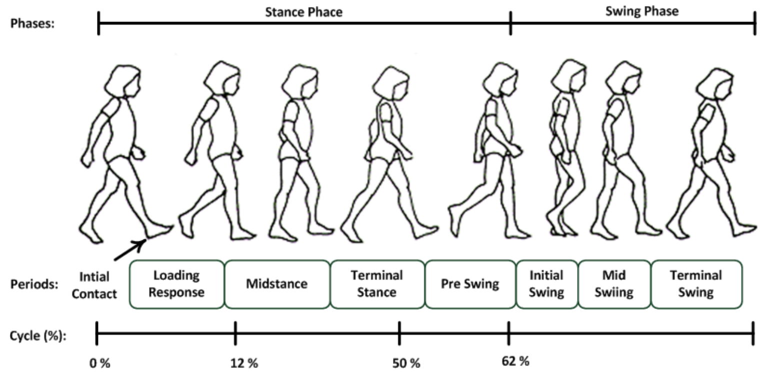

Figure 1: Division of the gait cycle into five stance phase periods and two swing phase periods [3].

the number of light or dark pixels; or background segmentation, which performs a simple background subtraction could be some of the possible ways to identify a person.

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

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

This paper is structured as follows: Section 2 gives a table overview research description of the accelerometer based gait analysis. The section surveys related papers and goes in deep details with the experiments, data acquisition, data analysis and comparison of results. Section 3 gives an description of how wearable gait recognition can be improved by proposing new methods for future work. Finally, section 4 shortly gives a summary of the paper.

2 Accelerometer Based Gait Analysis

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

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

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

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

Researching at different methodologies to analyzing the features of gait is increasing and become a popular area of research, especially in gait biometrics. Feature extraction from gait signals is a crucial for the efficient gait recognition. For a general gait analysis the signal processing flow is shown in Figure 2.

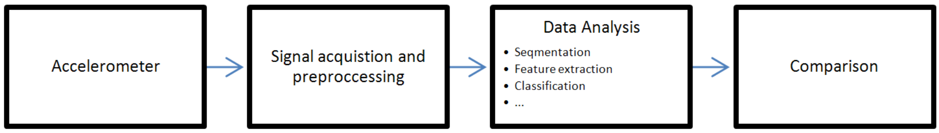

Figure 2: Signal processing flow of method for gait verification/identification.

Experiments

To the best of our knowledge, no public database has been created for accelerometer based gait recognition. However, researchers have made own experiments and databases. Table 1 summarizes experiments performed in research with the type of activity performed, environment and the range of walking per subject.

Table 1: Experiments Summary.

Study	Walking activities	Environment	Range (meter)
[9]	different speed	indoor hospital	10
[10]	normal	indoor	20
[11]	normal	indoor	100
[12]	normal, fast, slow	long corridor (stone plates)	50
[13][14]	normal	indoor	30
[15]	treadmill (normal, fast, slow)	-	-
[16]	free normal,fast,slow	overall	-
[17]	normal, fast, slow, circle	hall (solid surface)	20 m

All of the mentioned experiments above except [16] are *controlled experiment*. A controlled experiment is a fixed laboratory setting and furthermore differs from a real world scenario. People usually place their cell phone into their pockets or holding it while the phone is continuously moving in different directions. The mobile phone rotates and is in much more use. In the fixed setting the phone is usually attached one place to the body at all times.

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

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

Finally, very few studies have researched gait-recognition with different behavioral settings. A study [17] have shown that the gait-signal of one person slightly changes from one day to another.

Data acquisition

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

Table 2 gives an overview of the placement of sensors and sensor models that have been used in literature.

Table 2: Data Acquisition Summary.

Study	Acquistion From	Device
[18]	shoe	MEMS accelerometer
[19]	breast/hip	cell phone accelerometer
[20]	whole body weight	force plate
[11]	ankle/pocket/arm/hip	3D accelerometer (MRS)
[13][14]	waist	3D accelerometer (analog)
[21]	leg	wireless accelerometer (Tmote Sky)
[16]	pockets	phone handset
[22]	waist	3D accelerometer (ADXL05, analog)
[23][10]	waist	3D accelerometer (ADXL202JQ, analog)
[12]	hip	cell phone accelerometer
[15]	ankle	MEMS accelerometer
[9]	elastic belt on body	3D accelerometer
[24][17]	hip	3D accelerometer (MRS)

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

Preprocessing

Preprocessing has been performed differently in literature. Measured acceleration signals are sometimes low-frequency components. The signals that are being outputted are easily affected by experiment environmental noise, such as electronic noise in the equipment, high frequency noise etc., which will obscure/reduce the clarity of the acceleration data. Table 3 overviews preprocessing methods applied.

Data Analysis

Identifying users from gait patterns using accelerometers is based on the assumption that the gait acceleration profile (“template”) is unique to some extent for every person.

Table 3: Examples of Preprocessing Approaches

Study	Type	Approach
[11]	Time interpolation	Linear time interpolation
[17]	Noise filter	Weighted moving average
[13]	Noise filter	Daubeshies wavelet (wavelet transform)

First, a feature template vector that represents characteristics of the gait of the person to authenticate is computed and stored as the template. The same feature vector is computed during the authentication process and compared to the feature template.

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

Segmentation (Data Analysis)

Gait segmentation is the process of identifying ”boundaries” in the gait signal(s). Gait segmentation is an important sub-problem and can be performed in various ways. Gait signals obtained from an individual are composed of periodic segments called gait cycles. These cycles physically correspond to two consecutive steps of the individual. A gait cycle begins when one foot touches the ground and ends when that same foot touches the ground again as shown in Figure 3.

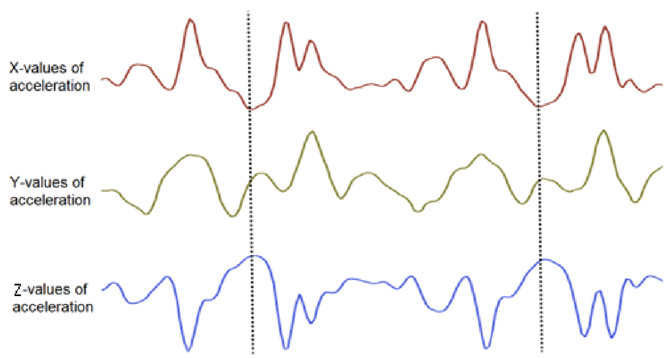

Figure 3: One gait cycle: begins when one foot touches the ground and ends when that same foot touches the ground again.

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

Table 4 summarizes three segmentation approaches that has been applied so far.

Table 4: Experiments Summary.

Study	Segmentation Approach
[23][10]	Cycle Detection Algorithm (1 step extraction)
[11][17]	Cycle Detection Algorithm (2 steps extraction)
[21]	Period of an periodic gait cycle

Feature extraction in the time domain (Data Analysis)

The time domain is a term used to describe the analysis of signals, with respect to time as mentioned earlier. The *average cycle method* was one of the first methods applied in gait biometrics within the time domain and also the most applied. The average cycle method is a simple approach that averages all cycles extracted. However, other extraction approaches have also been developed. Table 5 shows these extractions that has been developed until recently.

Table 5: Time Domain Feature Approaches

Study	Approach
[23]	Average cycle detection
[24]	Matrix with cycles
[10]	N-bin normalized histogram
[12]	Cumulants of different orders

Feature extraction in the frequency domain (Data Analysis)

Extracting features in the frequency domain is a bit different than in the time domain, since other (mathematical) approaches has to be applied. One of the best known is the fourier transform. A fourier fransform is a mathematical operation that transforms a signal from the time domain to the frequency domain, and vice versa. Table 6 shows an overview of other applied methods.

Table 6: Frequency Domain Feature Approaches

Study	Approach
[13]	Discrete fourier Transform (DFT)
[15]	Fast fourier Transform (FFT)
[25]	Discrete cosine Transform (DCT)
[20]	Discrete wavelet transform (DWT)
[19]	Wavelet packet decomposition (WPD)

Comparison functions (Data Analysis)

Usually when two feature vectors are compared to each other the use of a comparison function is applied. One example could be a distance metric function. In mathematics, the metric or distance function is a function which defines a distance between elements of a set. There are infinite numbers of distance functions developed. All depending on the metric, distance function give very different results. This has a major impact in the authentication and therefore it is important to find or create a suitable metric. In biometrics it is interesting in knowing the similarity of one person to another. Table 7 shows the comparison functions used.

Table 7: Comparison Approaches

Study	Comparison Metric
[23]	Cross-correlation
[11]	Absolute (manhattan) distance
[17]	Euclidean distance
[24]	Dynamic time warping (DTW)

Classification (Data Analysis)

Another well-studied area that is used within gait recognition is the (un)supervised learning approaches. Within wearable gait recognition, a supervised learning is a machine learning approach for deducing a function from gait signal training data. The training data consist of pairs of input objects, that are extracted from the accelerometer signals. The output of the function can be a continuous value, called regression, or can predict a class label of the input (feature vector), called classification. An overview is shown in Table 8.

Table 8: Classification Approaches

Study	Comparison Metric
[12]	Support Vector Machine (SVM)
[12]	Principal Component Analysis (PCA)
[21]	Linear Discriminant Analysis (LDA)
[18]	multilayer perception neural network
[19]	Kohonen self-organizing map (KSOM)

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

Comparing gait representations

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

In Table 9 is a short summary of current WS-based gait recognition studies from years 2004 to 2010 is shown. The last column, #TP, represents the number of test-persons.

Study	EER	Recognition	#TP
[26]	1.68	-	60
[11]	5 %	-	30
[27]	5.6 %	-	21
[24]	5.7 %	-	60
[17]	5.9 %	-	60
[23]	6.4 %	-	36
[10]	7.0 % , 19.0 %	-	36
[28]	13.7 %	-	31
[29]	-	96.93 %	9
[29]	-	96.93 %	9

Table 9: Performance of current wearable sensor-based gait recognitions. Excerpt of best EER from each author.

3 Discussion and Future Directions

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

Experiment Proposal:

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

Time is an important factor in an experiment. The more time one experiment last, the more data will be retrieved. To this, a subject must wear the attached accelerometer device over longer time. In addition, the subject should be experimented in different types of activities (activity recognition). Recently [16] analyzed activity recognition, unfortunately with few volunteers. Thus, it is strongly proposed that different activities are performed during the experiments.

As seen in Table 9 the numbers of subjects participating in experiments are very dissimilar. Experiments with low number of subjects statistically gives imprecise estimations when calculating recognition rates.

Clothes wearing might have an influence on the gait-appearance. This has to be further researched. Another issue related to clothes wearing is shoe wearing. As has been seen in work of [11], shoes slightly changes gait from one person to another. Therefore, several types of walking settings most be applied including abnormal behaviors.

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

Data Analysis Proposal:

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

Lately, a paper was written by [26] applying the use of principal component analysis (PCA) to wearable sensor based gait recognition and as an additional step in the Average Cycle Method. The PCA is mostly used in the exploratory data analysis and was known to give good recognition rates, it has been used in machine vision based gait recognition before. An EER of 1.68% was achieved during the work. This is an great improvement by around a factor of 3.5 compared to the best known results on the same private database. A strong suggestion for further improvements in performance is to look closer at different distance metrics since most simple metrics have been investigated. The merit of these results is not only the improvement of the gait recognition performance, but this can also be seen as a first step to a combination of recognizing not only that a person is walking (as opposed to for example sitting, running, cycling, etc.), but also who the person is (either identifying or authenticating that person).

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

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

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

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

4 Conclusion

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

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

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