Unobtrusive User-Authentication on Mobile Phones using Biometric Gait Recognition

Mohammad O. Derawi*, Claudia Nickel†, Patrick Bours* and Christoph Busch*
* Norwegian Information Security Lab., Gjøvik University College, Norway
* Email: {firstname}.{lastname}@hig.no
† Hochschule Darmstadt, University of Applied Sciences (CASED)
† Email: c.nickel@fbi.h-da.de

***Abstract*—The need for more security on mobile devices is increasing with new functionalities and features made available. To improve the device security we propose gait recognition as a protection mechanism. Unlike previous work on gait recognition, which was based on the use of video sources, floor sensors or dedicated high-grade accelerometers, this paper reports the performance when the data is collected with a commercially available mobile device containing low-grade accelerometers. To be more specific, the used mobile device is the Google G1 phone containing the AK8976A embedded accelerometer sensor [1]. The mobile device was placed at the hip on each volunteer to collect gait data. Preproccesing, cycle detection and recognition-analysis were applied to the acceleration signal. The performance of the system was evaluated having 51 volunteers and resulted in an equal error rate (EER) of 20%.**

***Index Terms*—gait recognition, mobile devices**

I. Introduction

Mobile devices – mobile phones, PDAs etc. – can be found in almost everyone's pocket and are considered as an essential tool in human-being's everyday life. They are not only used for mere communication such as calling or sending text messages; however, these devices are also used in applications such as internetting, receiving and sending emails and storing (sensitive) documents. As a result of this, not only phone numbers and addresses are stored in the mobile device but also financial information and business details which definitely should be kept private. Thus the value of the data on the phone is often higher than the pure costs of the phone itself and therefore this data should be protected. Most mobile phones do only offer authentication methods where the user has to remember a number (PIN) which he explicitly has to enter. This is not very user friendly, so many users decide to demand this authentication only once when the phone is switched on. A survey [2] shows that 66% of the respondents use PIN-authentication only at switch on and only 18% of the user also utilize the standby mode authentication. As a consequence, when a phone is lost or stolen, in most cases, all data on the phone is directly available to the new holder. This situation can be improved by offering an unobtrusive authentication method to users of mobile phones. As this authentication is no extra-work for the user but happens unnoticed to him, it is likely that more people would demand an authentication after a standby period. Biometric gait recognition based on accelerometer data is such an unobtrusive authentication method. When the owner of the phone is walking, the phone will recognize him based on his gait, so he can directly use the phone without any further authentication. When he is not walking, an alternative, active authentication method (e.g. PIN) can be used. In this paper, biometric gait recognition based on accelerometer data collected using the intrinsic sensors of the mobile device will be further explained and analyzed.

Different biometric characteristics such as fingerprints [3] already have been proposed to improve security of mobile devices. Biometric characteristics have the advantage that, unlike passwords, PINs, tokens etc., they cannot be stolen or forgotten. The main advantage of biometric authentication is that it establishes an explicit link to the subject's identity because biometrics use human physiological and behavioral characteristics. Most of these characteristics require an explicit user action when used for authentication, e.g. putting the finger on a fingerprint scanner. In contrast to this, our proposed method is unobtrusive because the relevant data is continuously recorded while the person is walking. These days many mobile devices already contain accelerometers that can be used to record the way a person walks.

Early studies from psychology [4], medicine [5] and biometrics [6], [7] already give evidence that human gait contains very distinctive patterns that can be used for identification and verification purposes.

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

The rest of the paper is structured as follows: Section II gives an overview over different existing gait recognition techniques. Section III gives a description of the accelerometer embedded in the phone and in section IV the used definitions are given. Section V describes the collection of gait data. In section VI the methods applied for feature extraction are described and the results are given in section VII. Section VIII gives conclusions and in the last section (IX) the future work is outlined.

II. Gait Recognition

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

In the machine vision approaches [8], [9], [10], [11], the system will typically consist of several digital or analog cameras with suitable optics for acquiring the gait data. Techniques such as background segmentation are used to extract features to identify a person. This technique is especially useful for surveillance scenarios.

In the floor sensor approach [12], [13], the sensors are placed on the floor which makes these methods suitable for controlling access to buildings. When people walk across the mat, they can be authenticated e.g. by the force to the ground which is measured by the mat.

The newest of the three approaches is based on wearing motion recording sensors on the body in different places: on the waist, in pockets, shoes and so forth. As our proposed method belongs to this group, it is explained in more detail here.
The wearable sensors (WS) can be accelerometers (measuring acceleration), gyro sensors (measuring rotation and number of degrees per second of rotation), force sensors (measuring the force when walking) etc. Table I gives an overview of current WS-based gait recognition studies from years 2004 to 2008. The last column, #TP, represents the number of test-persons.

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

The main advantage of gait recognition using accelerometers is that it provides an unobtrusive authentication method for mobile devices which already contain accelerometers (like mobile phones, PDAs etc.). Therefore, it can be applied for continuous verification of the identity of the user without his intervention. This is a great advantage to other biometric systems like fingerprint or face recognition which are also suitable for implementation on mobile phones but require active user intervention. This advantage of accelerometer based gait recognition compensates the so far worse recognition rates. For example, the equal error rate (EER) of fingerprint recognition [21] or 2-dimensional face recognition [22], compared to gait recognition, achieve lower EERs.

As biometric gait recognition only works when the user is walking, this method has to be combined with another authentication method. In [23] Vildjiounaite et al. propose a cascaded fusion of gait, voice and fingerprint. The active authentication via fingerprint is only required when the two unobtrusive authentication methods fail. This happens in $10-60\%$ of the cases and indicates that adding an unobtrusive authentication method to mobile phones does decrease the neccessatity of regular active authentication and hence increases the user friendlyness.

III. Accelerometer

The G1 has an integrated sensor (AK8976A) for measuring acceleration in three axes [1]. This sensor is a piezoresistive MEMS (Micro-Electro-Mechanical-System) accelerometer which uses piezoresistors to measure the accelerations. Piezoresistors have the property that they change their resistance on tension and compression. The sensor consists of a cantilever beam which deflects from its neutral position under acceleration. This deflection is measured using piezoresistors. See Figure 1 for a schematic diagram of this principle [24]. Acceleration in all directions can be measured by combining three sensors perpendicular to each other such that they span the three-dimensional space.

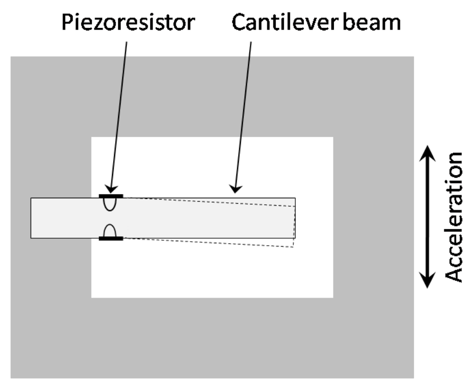

Fig. 1. Schematic diagram of a piezoresistive accelerometer.

IV. Definitions

In the following we give the definitions used in this paper: A *go* starts when the recording of the data has been started and ends when recording has been terminated. In other words, everything stored in one file on the phone is one go, including attachment and detachment of the phone and the standing - turning around - standing at the end of the corridor. See section V for more details about data collection. Figure 2 shows the plot of one go. One can see that two *walks* can be extracted from one go. One walk contains only data when the person is walking. It begins when the person starts walking and ends when he/she stops at the other end of the corridor. One walk contains several steps of one subject. There is a periodic repetition every two steps which is called one *cycle* [6].

V. Data collection

The data used in this article is collected using a standard G1 mobile phone which does contain accelerometers as described in section III. The G1 uses the android platform and a software was written for this platform to access the accelerometer and output the data from the sensor to a file (40-50 samples per second for each of the three directions x, y and z). While recording the gait data the phone has been placed in a pocket

Study	Sensor Location	EER	Recognition	#TP
Holien [14]	left leg (hip)	5.9 %, 25.8 %	-	60
Gafurov et al. [6]	ankle	5 %	-	30
Gafurov et al. [6]	trousers pocket	7.3 %	-	50
Gafurov et al [6].	hip	13 %	-	100
Gafurov et al. [6]	arm	10 %	-	30
Morris [15]	shoe	-	97.4 %	10
Huang et al. [16]	shoe	-	96.93 %	9
Ailisto et al.[17]	waist	6.4 %	-	36
Mäntyjärvi et al. [7]	waist	7.0 % , 19.0 %	-	36
Rong et al. [18]	waist	6.7 %	-	35
Rong et al. [19]	waist	5.6, 21.1 %	-	21
Vildjiounaite et al. [20]	hand	17.2, 14.3 %	-	31
Vildjiounaite et al. [20]	hip pocket	14.1, 16.8 %	-	31
Vildjiounaite et al. [20]	breast pocket	14.8, 13.7 %	-	31

TABLE I
PERFORMANCE OF CURRENT WEARABLE SENSOR-BASED GAIT RECOGNITION SYSTEMS. MODIFIED FROM [6].

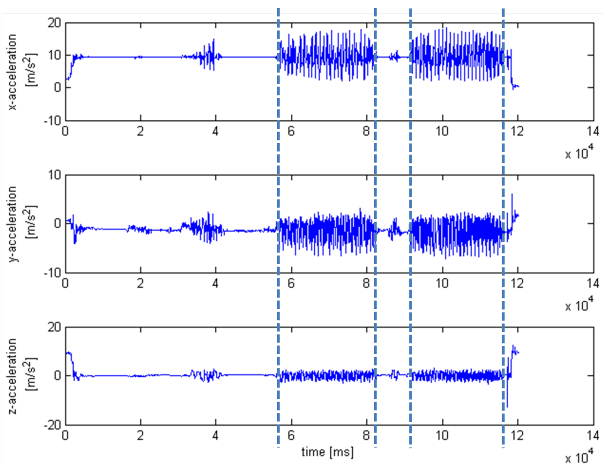

Fig. 2. Sample data collected with the G1. The acceleration in x-, y- and z-direction collected during one go is shown, including attaching the phone etc. The dotted lines show the walking part of one go.

attached to the belt of the subject on the right-hand side of the hip. The phone is positioned horizontal, the screen points to the body, the upper part of the phone points in walking direction (see figure 3).

Fig. 3. Phone attached to subject and the three axes in which acceleration is measured.

The walking distance was about 37 meters down the hall on flat carpet (see figure 4). At the end of the hall the subjects had to wait 2 seconds, turn around, wait again and then walk back the same distance.

Fig. 4. Photograph of the walking setting.

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

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

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

	< 20	$20-24$	$25-30$	> 30	unknown
male	1	2	26	10	2
female	0	5	4	0	1
total	1	7	30	10	3

TABLE II
AGE AND GENDER DISTRIBUTION OF VOLUNTEERS.

VI. FEATURE EXTRACTION

The raw data retrieved from the mobile phone needs to be processed in order to create robust templates for each subject.

The program for data analysis has been developed in Java and is based on the work of [14]. Of the three different signals retrieved from the phone only the acceleration in x-direction is used as it showed to give the best results. From this raw data the repeating cycles are extracted to result in one single average cycle for each person. A brief description of the steps conducted for feature extraction is given in the following:

- *Time Interpolation:* Due to the android SDK, the phone only outputs data values whenever there is a change in the sensor. Therefore, the time intervals between two sample points (acceleration values) are not always equal, which requires time interpolation. This ensures that the time-interval between two sample-points will be fixed.
- *Filtering:* Removal of noise is done by applying a weighted moving average (WMA) filter.
- *Average Cycle length:* From the data it is known that the cycle length is between $40 - 60$ samples. To compute the average cycle length a small subset from the center of the data is extracted and compared with other subsets of similar length. Based on the distance scores between these subsets, the average cycle length is computed.
- *Cycle Detection:* The cycle detection starts from a minimum point $P_{start} = P_{min}$ around the center of the walk. From this point, cycles are detected in both directions. By adding the average length to P_{start}, the estimated ending point $P_{end} = P_{start}+averageLength$ is retrieved (in opposite direction: $P_{end} = P_{start} - averageLength$). The cycle end is defined to be the minimum in the interval of +/- 10% (of the average cycle length) from the estimated end point, see figure 5. This process will be repeated from the new end point until all cycles are detected.

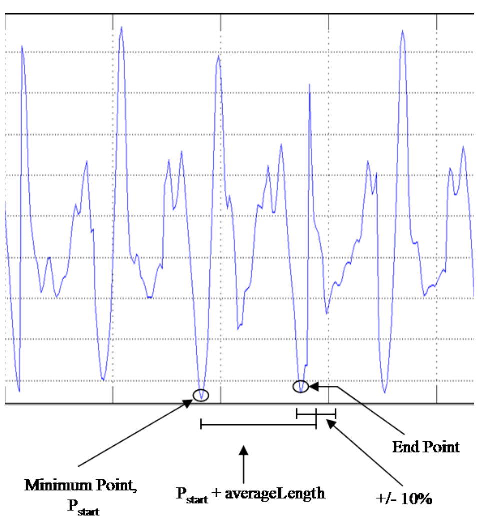

Fig. 5. Cycle Detection

- *Average Cycle:* Before the average cycle is computed, irregular cycles are omitted. This is done by using Dynamic Time Warping (DTW) [25] to calculate the distances between all cycles and deleting the ones which have an unusual large distance to the other cycles. The cycle with the lowest average DTW-distance to the remaining cycles will be used as the average cycle. This average cycle, which is a vector (of real values) of an average length around 45 samples, will be used as the feature vector for this walk.

VII. Results

The quality of the feature vector extracted as described in section VI was analyzed. The distance metric used to compare two feature vectors was Dynamic Time Warping, which was chosen because the feature vectors by nature can have different lengths. By using DTW we avoid normalizing the feature vectors to a fixed length. The performance is measured in terms of False Match Rate (FMR) versus False Non-Match Rate (FNMR) and the results are graphically displayed using a DET (Detection Error Trade-off) curve in figure 6.

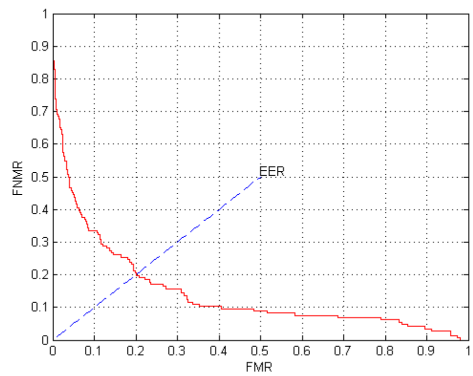

Fig. 6. DET-curve: Performance of Gait Recognition with an EER of 20.1 %.

Comparing the achieved equal error rate of 20.1% to the error rate for the same analysis settings stated in Holien's work (12.9%) [14], one can see an increase of approximately 50%. An issue that needs to be taken into consideration is that the test data used in this paper was collected using a mobile phone which contains a lower sampling rate accelerometer. Its sample rate was around $40 - 50$ samples per second whereas the high quality dedicated accelerometer used in Holien had around 100 samples per second.

VIII. Conclusion

The main contribution of this paper was to demonstrate that one has the ability to use commercial mobile phones equipped with accelerometers to carry out biometric gait recognition. As stated before, the advantage of this method to other biometric systems which could be implemented on mobile phones, is the unobtrusive operation which gives a high user friendliness.

To the best of our knowledge, for the first time, data collected by accelerometers in a standard mobile phone was used for biometric gait recognition. A feature extraction method was adapted and applied to the data from 51 volunteers collected in two sessions. The achieved EER of 20.1% is approximately 50% higher than the EER achieved with a similar method using a dedicated accelerometer with a twice as high sampling rate. To make biometric gait recognition using embedded accelerometers a technology suitable for practical use, further research on feature extraction and comparison is required. However the achieved results are promising and the proposed approach contains potential for enhancement.

IX. Future Work

The obtained equal error rate of 20.1% indicates that biometric gait recognition can be run on mobile phones but it is not yet ready for practical use. Focus of our future work will be enhancing the cycle extraction technique to get more reliable feature vectors.

In addition to improving the recognition rates for normal walk on flat ground, future work will include analysis of different settings to create a gait recognition method which provides robust verification under different circumstances. These circumstances might be different walking conditions like walking speed or ground which will have an influence of the walk of a person and therefore might also influence the biometric recognition. Therefore, accelerometer data of the subjects will be recorded at several settings like different walking speeds and different grounds (e.g. carpet, grass, gravel).

In addition, data will be collected using phones at different positions (e.g. front and back trousers pocket and pocket attached to belt) for further analysis. To handle the movements of the phone when carried in a trousers pocket, values recorded by the magnetic field sensor can be used to normalize the orientation of the phone.

The attack resistance of biometric gait recognition should also be analyzed. Studies by Gafurov [6] and Mjaaland [26] show that it is difficult for an attacker to imitate another person. This needs to be confirmed for the special scenario of mobile phones.

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