# Identifying people from gait pattern with accelerometers

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# Identifying People from Gait Pattern with Accelerometers

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## ABSTRACT

Protecting portable devices is becoming more important, not only because of the value of the devices themselves, but for the value of the data in them and their capability for transactions, including m-commerce and m-banking. An unobtrusive and natural method for identifying the carrier of portable devices is presented. The method uses acceleration signals produced by sensors embedded in the portable device. When the user carries the device, the acceleration signal is compared with the stored template signal. The method consists of finding individual steps, normalizing and averaging them, aligning them with the template and computing cross-correlation, which is used as a measure of similarity. Equal error rate of 6.4% is achieved in tentative experiments with 36 test subjects.

Keywords: Biometrics, gait, accelerometer, mobile phone, portable, PDA.

## 1. INTRODUCTION

Portable devices, such as smart phones and personal digital assistants (PDAs), wearable computers, intelligent clothing and smart artifacts are becoming a part of our everyday environment. Their importance, and thus also the risk associated to them is increasing. For example, personal portable devices are being used for communication, remote transactions and as means of storing valuable and discrete data. Yet, the protection of these devices is usually poor, especially in "on" state, when not even the four digit PIN code protects the information and the device[1]. Clearly, there is an opportunity for an unobtrusive, implicit security mechanism. In this paper a biometric method for creating such a mechanism is presented, namely we describe a novel method for verifying the identity the users of portable devices while they walk with the devices. Identifying the user of a portable device by gait is very natural, unobtrusive and it complies to the paradigm of calm computing[2] where the user should not be disturbed or burdened by the technology she is using.

Walking style, or gait, is known to differ between individuals[3] and to be fairly stable, where as deliberate imitation of an other person's walking style is difficult. Automatic gait recognition has been studied as a behavioral biometric for about a decade[4]. Typically, vision based methods are used for gait recognition[4-7]. Generally, the performance of gait biometrics is lower than, e.g. fingerprint biometrics, and the method is in its infancy[8].

Gait recognition has not been suggested for securing personal devices, their communication capability and data contained in them. Instead, various other biometric modalities have been proposed and used for this purpose, including signature[9], voice[10,11] and fingerprints, which has been employed in a commercial PDA device[12]. All these approaches - except voice recognition - require explicit actions by the user, e.g. giving fingerprint or writing on a touch screen, in order to be accepted as a user. In this sense the methods are obtrusive and require attention.

In this paper a new identification method[*] for personal devices is presented, which uses the acceleration signals produced by normal walking. The presented method differs significantly from the mainstream gait recognition research relying on computer vision[5-7] or sensors installed in the floor[13]. To our knowledge there are no papers published on the

[*] Patent pending.

gait identification using acceleration sensors. The person identification approach can be seen as reversal of the research attempts to recognize activities, e.g. walking, running or cycling, independent of the user[14]. Lester and co-workers have reported an accelerometer based system for detecting if two devices are carried by the same person at the same time[15], which is somewhat akin to our approach.

The method operates on the background and is thus unobtrusive and does not require the user's attention. As acceleration sensors become more common place in portable devices[**], there will be no extra hardware cost associated with the gait identification method presented here.

There is a growing concern among the public and experts about the threats associated with widespread use of biometrics[16]. The perceived threats are loss of privacy on the one hand and the possibility of identity theft on the other. The gait based identification method presented in this paper gives at least partial answer to both of these questions: the privacy of the biometric data is preserved by the fact that it is stored in medium controlled by the user herself, namely the portable device; the perceived threat of an identity theft is less eminent than in the case of, say, fingerprints.

## 2. GAIT RECOGNITION METHOD

### 2.1. Overview of the method

The principle of identifying users of portable devices from gait pattern with accelerometers is presented in Figure 1. The three-dimensional movement produced by walking is recorded with a 3-D accelerometer device worn by the user.

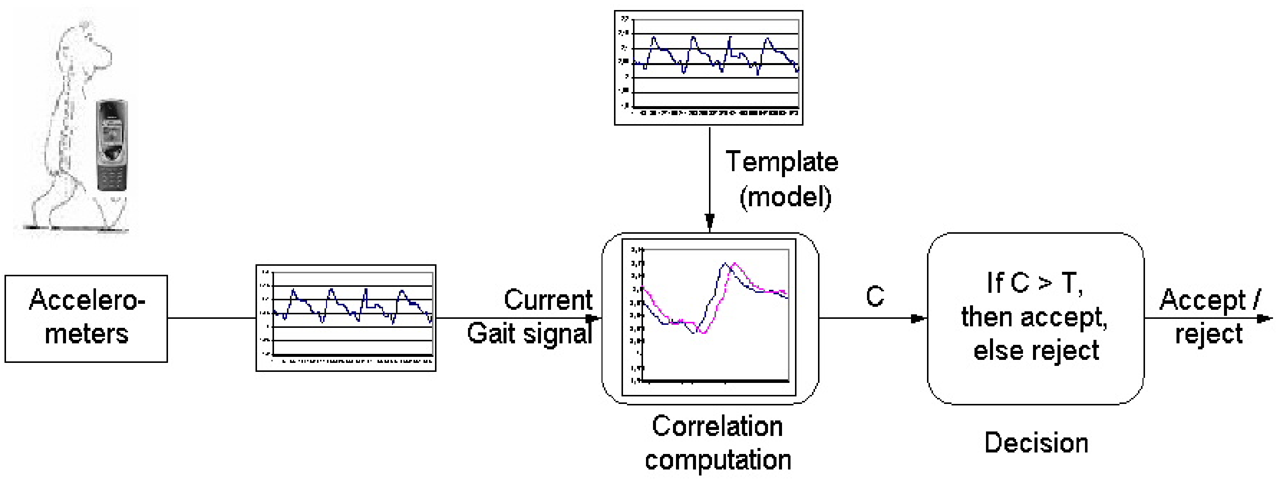



Figure 1: Block diagram of the gait based verification method

In the training phase the three-dimensional acceleration signals associated with the walking pattern are divided into one step long parts. Since the right and left steps are not symmetrical, they are processed separately, as "*a*" and "*b*" steps. However, we do not try to identify "right" and "left". The steps are found in all three signals, x, y and z by searching local minima and maxima. Steps belonging to both groups are normalized in length and amplitude and then averaged. The averaged x (forward), and z (vertical) acceleration signals for *a* and *b* steps form the biometric template which we call the **gait code**. Horizontal signal y is not used since it is proved to be less permanent than x and z signals in our experiments. An acceleration signal for vertical direction is shown in Figure 2 with first steps *a* and *b* shown as *Step_a1* and *Step_b1*.

[**] For example, Nokia 5140 phone can be equipped wit a "Fitness Monitor" measuring acceleration.

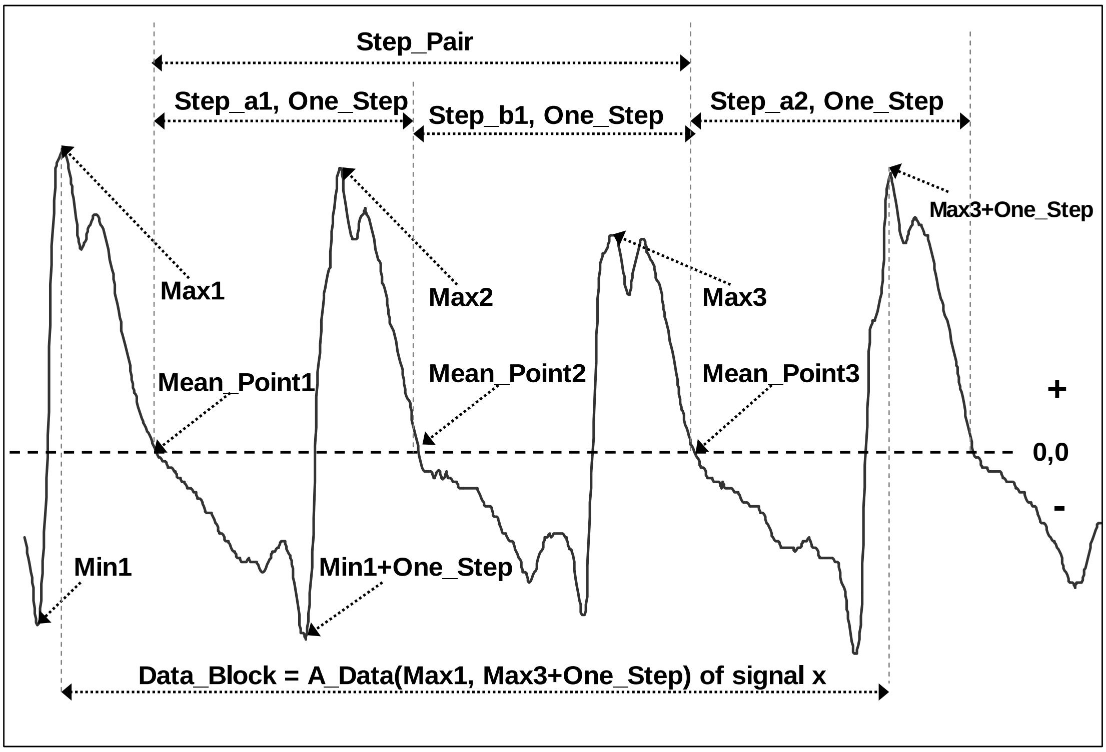



Figure 2. A time domain signal x of acceleration gait data with the main parameters used in gait code extraction.

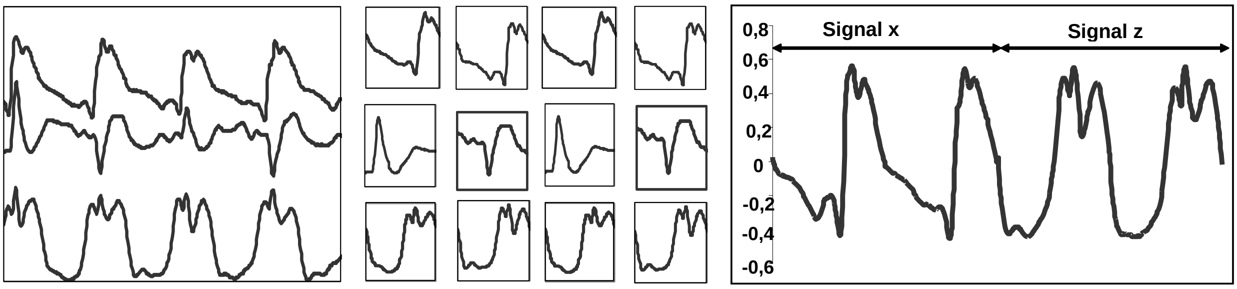
The identification phase starts with the generation of current *c* and *d* gait codes as in training phase. After that, comparison of the current gait codes with the enrolled gait codes is performed with cross correlation method. The correlation coefficients of x and z signals are averaged giving a figure of similarity, *C*. If *C* is larger than a pre-set threshold *T*, verification is accepted, otherwise it is rejected. The method is summarized in Table 1.

Table 1: Gait recognition method

| **Enrolment** |
|---|
| 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*] |
| **Identification 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 |

### 2.2. Detailed algorithm description

When acceleration data is used for identification the gait code made out of the acceleration signals is needed. A time domain signal x of acceleration gait data is depicted in figure 2, where the main parameters used in the description of the gait code extraction are explained. The gait code is made by first separating all individual steps *Step_a* and *Step_b* of the acceleration signals in blocks of two consecutive steps, normalizing the length of each individual step, averaging 60% of the best, or of the most representative *steps a* and *b* and, finally, normalizing the amplitude of the averaged steps and concatenating the averaged data. Part of the x, y and z signals of acceleration data is shown in figure 3.a), separated individual steps in figure 3.b) and final gait code vector in figure 3.c). Presently we combine two of the least volatile signals, x and z, into the gait code to represent the whole data. Signal y is also processed for possible future utilization but it is not included in the final gait code. The explanatory pseudocodes, used in the following description, are marked with (Table2.1), (Table2.2),…(Table2.9) and are found in Table 2.




a) b) c)

Figure 3. a) Signals x, y and z in descending order. b) Individual steps. c) Final 512 byte long gait code vector.

The gait code extraction begins by calculating an initial **average length** of one step, *One_Step*, from the acceleration data, *A_Data*. The gait code must represent steps *a* and *b*, so we look for two consecutive steps, or one *Step_Pair*, to gain meaningful data. We begin the search by looking for the first minimum point, *Min1* (Table2.1), within first *One_Step* points in signal x of *A_Data*. We use signal x since it has a relatively unambiguous wave form. Then we search for a local maximum point, *Max1* (Table2.2), which is the starting point for the search of the *Step_Pair* (and also of step a). *Max1* should occur somewhere between *Min1* and *(Min1+One_Step)* since the maximum part of any step *a* or *b* situates between two consecutive minima. *Max2* marks the location where the search for starting point of step *b* (end point of step *a*) begins and *Max3* is, in a similar manner the preliminary end point of *Step_Pair* (and the end point of step *b*). *Max2* is found as shown in (Table2.3) and *Max3* is found in the same way.

Table 2: Explanatory pseudocodes for gait recognition method

| | |
|---|---|
| 1. | Min1 = find_local_minimum_within(A_Data(1, One_Step)) |
| 2. | Max1 = find_local_maximum_within(A_Data(Min1, Min1+One_Step)) |
| 3. | Max2 = find_local_maximum_within(A_Data(Max1+0.9*One_Step, Max1+1.1*One_Step)) |
| 4. | Data_Block = A_Data(Max1, Max3+One_Step) |
| 5. | Mean_Data = Data_Block – average(Data_Block) |
| 6. | Mean_Point1 = from_plus_to_minus(Mean_Data(Max1+0.1*One_Step, Max1+0.5*One_Step)) |
| 7. | Similarity_a1 = corr(**Step_a1**, Step_a2) + corr(**Step_a1**, Step_a3) +…+ corr(**Step_a1**, Step_aN) |
| 8. | x_a_Mean = average_and_normalize(Step_a's of signal x with the highest Similarity_a) |
| 9. | Gait_Code = [x_a_Mean, x_b_Mean, z_a_Mean, z_b_Mean] |

If the local maxima, *Max1*, *Max2* and *Max3* were unambiguous, we could separate all the following *Step_Pairs* in all signals x, y and z as above. Unfortunately, there may be one or more side peaks nearby the local maxima, which can sometimes turn out to be the local maxima looked for. The same is true for local minima, as well. This makes it difficult to find the equivalent relative *Max1*, *Max2* and *Max3* locations and, consequently, the same starting and end points for *Step_Pairs*. If starting and end points differ, meaningful data averaging for gait code is, in practice, impossible.

To overcome this difficulty we use the descending slopes of the signal following the points *Max1*, *Max2* and *Max3* where we look for points *Mean_Point1*, *Mean_Point2* and *Mean_Point3* which have the average value of *Data_Block* (Table2.4). The length of *Data_Block* is a three times *One_Step* long part of signal x inside which one *Step_Pair* must situate. For one *Step_Pair* the three consecutive *Mean_Points* are: the beginning of the step a (*Mean_Point1*), the end of step a or beginning of step b (*Mean_Point2*) and the end of step b (*Mean_Point3*). To find *Mean_Points* we need the averaged *Mean_Data* of the *Data_Block* (Table2.5) where we look for the points of transition from positive to negative value after *Max1*, *Max2* and *Max3*.

The descending slope is not the only location where values similar to *Mean_Points* can exist. That's why the search area inside the *Mean_Data* must be limited. The first mean point, *Mean_Point1* is found as in (Table2.6) and *Mean_Point2* and *Mean_Point3* are searched for in a similar manner. Now the first *Step_Pair*, with the limits of steps a and b known, is confined and the corresponding *Step_Pairs* of *A_Data* in signals y and z are separated with the indices of the signal x *Mean_Points*. The process for all the next *Step_Pairs* is the same except that the length of the *One_Step* is continuously updated and *Min1* is not needed anymore.

With all N *Step_Pairs* found we can construct the gait code. First the lengths of all the *Step_Pairs* are normalized to 256 points by normalizing *Step_a* and *Step_b* of each *Step_Pair* to 128 points. To find the most representative gait code we correlate all the *Step_a* steps against each other and the correlation coefficients are added to form a similarity value, *Similarity_aN* (Table2.7). The same is done for all the *Step_b* steps and for all signals x, y and z. Then 60 % of the steps with the highest similarity values are chosen, they are averaged and the amplitude of the averaged result is normalized between [-0.5 , +0.5] to form the mean step as shown for step a of signal x in (Table2.8). Finally, the biometric template, or the gait code is created by concatenating the averaged and normalized representations of steps *a* and *b* of signals x and z to the 512 points long gait code vector (Table2.9).

The gait code is calculated similarly for enrolment and identification data. Since the order of the steps (left-right or vice versa) in the enrolment and identification data is not known the enrolment gait code is calculated twice. First enrolment gait code is calculated as beginning from *Step_a1* and the second enrolment gait code beginning *One_Step* further, from *Step_b1*. Now the first enrolment gait code is of the form *a-b-a-b* and the second of the form *b-a-b-a*, both with x signal steps first following with z signal steps (Table2.9). After this "step interchange" we can reliably compare the claimant gait code to both forms of enrolled gait codes of all the enrolled persons. The comparison is carried out by correlating all the four individual claimant gait code steps (Table2.9) separately against corresponding enrolment gait code steps and adding up the four correlation coefficients to form the score value. An example of four enrolled gait codes (enrolled 1, 2, 3 and 4) and one claimant gait code (claimant x) is shown in figure 4. The gait code of claimant x is similar to enrolled person 4.

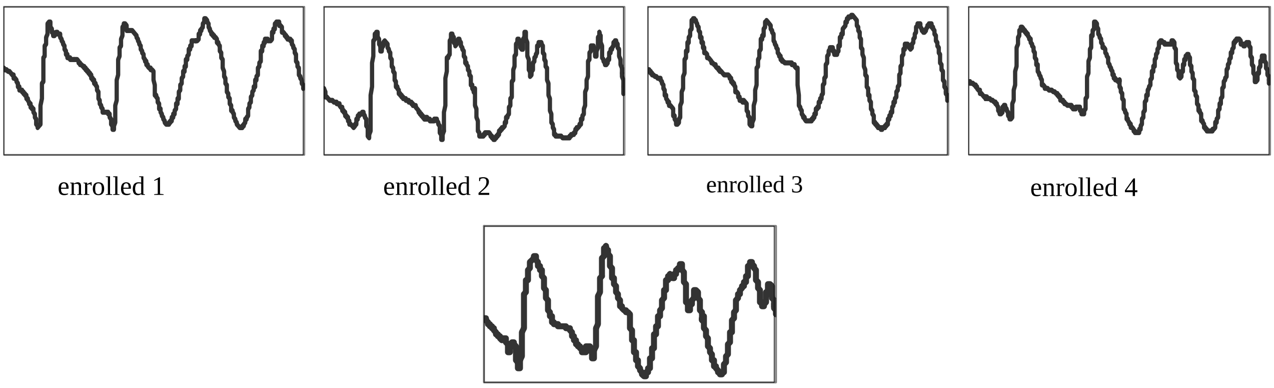



Figure 4: Comparison of claimant gait code to enrolled gait codes. The gait code of claimant x is similar to enrolled person 4.

## 3. EXPERIMENTS

### 3.1. Experimental set-up

An experiment was performed in order to evaluate the potential of the proposed method. The test set-up consisted of a portable device which the user wore on a belt, in a way similar to carrying a mobile phone or a PDA in a holster. The device contained a three-dimensional accelerometer (composed of two perpendicularly positioned Analog Devices ADXL202JQ accelerometers), and it was worn in the same position, behind at the waist, by all the users: x-axis pointed forward, y-axis to the left and z-axis up. The accelerometer signals were recorded with 256 Hz frequency using a laptop computer equipped with National Instruments DAQ 1200 card carried by the tester. The experimental system is shown in the photograph in Figure 5.

Figure 5: The experimental system for gait acceleration data collection.

The number of test subjects was 36, of which 19 were male and 17 female, all adults. Each test subject walked about 20 m. The experiment was repeated after five days to get a second data set consisting of three samples, about 20 m each.

### 3.2. Tentative results

The experiment contained 3 x 36 = 108 genuine trials, in which the templates (day-one) were compared against current signals (day-two). Likewise, 1296 impostor trials were produced (here we compared each enrolment sample with 35 impostor samples from day-two). The performance of the method was measured in terms of False Acceptance Ratio (FAR), False Rejection Ratio (FRR) and Total Error Rate (TER), which is the sum of the two former. The FAR, FRR and TER are given for certain values of the threshold $T$ (correlation coefficient) in Table 3. The lowest TER (12%) is given when FAR=6.4% and FRR=5.4%. The equal error rate (EER) is 6.4%. The Receiver operating characteristics curve in terms of Genuine Acceptance Rate (GAR) and FAR is presented in Figure 6.

The tentative results with 36 test subjects show that identifying people by their gait using accelerometers worn by them is possible. Although these results are very promising, it is clear that they must be improved for making practical applications feasible. Therefore, we plan to work on other methods employing acceleration signals, such as amplitude histogram statistics and frequency domain methods, fusing them with correlation results in order to still improve the identification performance.

Table 3. T, FAR, FRR and TER

| T | FAR | FRR | TER |
|---|---|---|---|
| 0,955 | 0,19 | 0,03 | 0,22 |
| 0,960 | 0,13 | 0,05 | 0,19 |
| 0,962 | 0,10 | 0,05 | 0,15 |
| 0,965 | 0,077 | 0,054 | 0,13 |
| 0,965 | 0,075 | 0,054 | 0,13 |
| 0,966 | 0,070 | 0,054 | 0,12 |
| 0,966 | 0,066 | 0,054 | 0,12 |
| 0,967 | 0,064 | 0,054 | 0,12 |
| 0,967 | 0,059 | 0,081 | 0,14 |
| 0,972 | 0,030 | 0,14 | 0,17 |

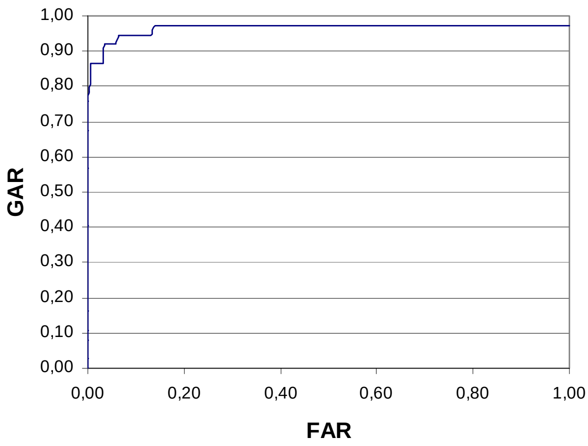



Figure 6: Receiver operating characteristics.

## 4. DISCUSSION

A novel method for recognizing the person carrying a mobile device has been presented in this paper. The recognition is based on the analysis of the three-dimensional acceleration signal produced by gait. Unlike the mainstream gait recognition methods, which rely on video imagery, this method employs acceleration sensors embedded in the portable device. The performance of the new method is at the same level or even better than those achieved by the video based gait recognition in recent studies[5, 7, 17, 18], which report correct (rank 1) results between 72% and 88%. It should be noted that these gait recognition methods differ not only in technical implementation but also in proposed application from the one presented here.

While video based gait biometrics are targeted for surveillance, security and forensic applications, the method presented here is mainly aimed for protection of personal devices, such as PDAs, smart mobile phones or even hand guns, of illicit use. Protecting PDAs and smart phones becomes increasingly important, since the value of the information stored in them and their capabilities for e-commerce, e-banking and other transactions will be more extensively used. With the advance of miniaturization, the method could be applied to USB tokens, memory cards and even smartcards (credit cards). The identification method is by nature unobtrusive, privacy preserving and controlled by the user. The biometric data, that is the acceleration signal, never leaves the user's device. It should be noted that we do not see the gait biometrics as the sole user authentication method for portable devices, but it should be backed up with traditional passwords or the like for exceptional situations. Fusing the results of accelerometer based gait biometrics with other biometric modalities, such handwritten signature recognition, which is a natural option for devices with touch sensitive screens, voice, natural especially in mobile phones, or fingerprint, would probably result in a performance better than any of the modalities alone.

The potential drawbacks of the method are partly common to all gait based methods: effect of changes in the speed of walking, change of shoes (e.g. from sneakers to high heels) and ground; also drunkenness and injuries affect gait. In the future, we must study the effect of carrying the personal device containing the accelerometers in different places and positions, such as pockets. These issues remain to be studied in future along with the development of the recognition along with the recognition algorithm.

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