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Title: Gait Recognition Using Wearable Motion Recording Sensors

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Research Article

Gait Recognition Using Wearable Motion Recording Sensors

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This paper presents an alternative approach, where gait is collected by the sensors attached to the person's body. Such wearable sensors record motion (e.g. acceleration) of the body parts during walking. The recorded motion signals are then investigated for person recognition purposes. We analyzed acceleration signals from the foot, hip, pocket and arm. Applying various methods, the best EER obtained for foot-, pocket-, arm- and hip- based user authentication were 5%, 7%, 10% and 13%, respectively. Furthermore, we present the results of our analysis on security assessment of gait. Studying gait-based user authentication (in case of hip motion) under three attack scenarios, we revealed that a minimal effort mimicking does not help to improve the acceptance chances of impostors. However, impostors who know their closest person in the database or the genders of the users can be a threat to gait-based authentication. We also provide some new insights toward the uniqueness of gait in case of foot motion. In particular, we revealed the following: a sideway motion of the foot provides the most discrimination, compared to an up-down or forward-backward directions; and different segments of the gait cycle provide different level of discrimination.

1. Introduction

Biometric recognition uses humans anatomical and behavioral characteristics. Conventional human characteristics that are used as biometrics include fingerprint, iris, face, voice, and so forth. Recently, new types of human characteristics have been proposed to be used as a biometric modality, such as typing rhythm [1], mouse usage [2], brain activity signal [3], cardiac sounds [4], and gait (walking style) [5]. The main motivation behind new biometrics is that they are better suited in some applications compared to the traditional ones, and/or complement them for improving security and usability. For example, gait biometric can be captured from a distance by a video camera while the other biometrics (e.g., fingerprint or iris) is difficult or impossible to acquire.
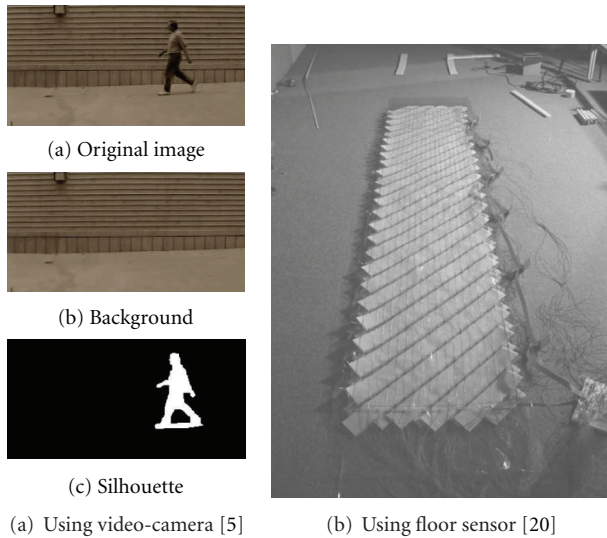
Recently, identifying individuals based on their gait became an attractive research topic in biometrics. Besides being captured from a distance, another advantage of gait is to enable an unobtrusive way of data collection, that is, it does not require explicit action/input from the user side. From the way how gait is collected, gait recognition can be categorized into three approaches:

(i) Video Sensor- (VS-) based,

(ii) Floor Sensor- (FS-) based,

(iii) Wearable Sensor- (WS-) based.

In the VS-based approach, gait is captured from a distance using a video-camera and then image/video processing techniques are applied to extract gait features for recognition (see Figure 1). Earlier works on VS-based gait recognition showed promising results, usually analyzing small data-sets [6, 7]. For example, Hayfron-Acquah et al. [7] with the database of 16 gait samples from 4 subjects and 42 gait samples from 6 subjects achieved correct classification rates of 100% and 97%, respectively. However, more recent studies with larger sample sizes confirm that gait has distinctive patterns from which individuals can be recognized [8–10]. For instance, Sarkar et al. [8] with a data-set consisting of 1870 gait sequences from 122 subjects obtained 78% identification rate at rank 1 (experiment B). A significant amount of research in the area of gait recognition is focused on VS-based gait recognition [10]. One reason for much interest in VS-based gait category is availability of large public gait databases, such as that provided by University of South Florida [8], University of Southampton [11] and

Table 1: Summary of some VS-based gait recognitions.

Study	EER, %	#S
Seely et al. [12]	4.3–9.5	103
Zhao et al. [13]	11.17	—
Hong et al. [14]	9.9–13.6	20
BenAbdelkader et al. [15]	11	17
Wang et al. [16]	3.8–9	124
Wang et al. [17]	8–14	20
Wang et al. [18] (without fusion)	8–10	20
Bazin et al. [19] (without fusion)	7–23	115

Table 2: Summary of several FS-based gait recognitions.

Study	Recognition rate, %	#S
Nakajima et al. [23]	85	10
Suutala and Röning [24]	65.8–70.2	11
Suutala and Röning [25]	79.2–98.2	11
Suutala and Röning [26]	92	10
Middleton et al. [20]	80	15
Orr and Abowd [27]	93	15
Jenkins and Ellis [28]	39	62

(a) Original image

(b) Background

(c) Silhouette

(a) Using video-camera [5]

(b) Using floor sensor [20]

(c) Using wearable sensor on the body [21]

Figure 1: Examples of collecting gait.

Chinese Academy of Sciences [22]. Performance in terms of EER for some VS-based gait recognitions is given in Table 1. In this table (and also in Tables 2 and 3) the column #S indicates the number of subjects in the experiment. It is worth noting that the direct comparison of the performances in Table 1 (and also in Tables 2 and 3) may not be adequate mainly due to the differences among the data-sets. The purpose of these tables is to give some impression of the recognition performances.

In the FS-based approach, a set of sensors are installed in the floor (see Figure 1), and gait-related data are measured when people walk on them [20, 24, 27, 28]. The FS-based approach enables capturing gait features that are difficult or impossible to collect in VS-based approach, such as Ground Reaction Force (GRF) [27], heel to toe ratio [20], and so forth. A brief performance overview of several FS-based gait recognition works (in terms of recognition rate) is presented in Table 2.

The WS-based gait recognition is relatively recent compared to the other two mentioned approaches. In this approach, so-called motion recording sensors are worn or attached to various places on the body of the person such as shoe and waist, (see Figure 1). [21, 29–34]. Examples of the recording sensor can be accelerometer, gyro sensors, force sensors, bend sensors, and so on that can measure various characteristics of walking. The movement signal recorded by such sensors is then utilized for person recognition purposes. Previously, the WS-based gait analysis has been used successfully in clinical and medical settings to study and monitor patients with different locomotion disorders [35]. In medical settings, such approach is considered to be cheap and portable, compared to the stationary vision based systems [36]. Despite successful application of WS-based gait analysis in clinical settings, only recently the approach has been applied for person recognition. Consequently, so far not much has been published in the area of person recognition using WS-based gait analysis. A short summary of the current WS-based gait recognition studies is presented in Table 3. In this table, the column "Reg." is the recognition rate.

This paper reports our research in gait recognition using the WS-based approach. The main contributions of the paper are on identifying several body parts whose motion can provide some identity information during gait; and on analyzing uniqueness and security per se (robustness against attacks) of gait biometric. In other words, the three main research questions addressed in this paper are as follows.

(1) What are the performances of recognition methods that are based on the motion of body parts during gait?

(2) How robust is the gait-based user authentication against attacks?

(3) What aspects do influence the uniqueness of human gait?

TABLE 3: Summary of the current WS-based gait recognitions.

Study	Sensor(s) location	Performance, %		#S
		EER	Reg.	
Morris [29]	shoe	—	97.4	10
Huang et al. [32]	shoe	—	96.93	9
Ailisto et al. [21]	waist	6.4	—	36
Mäntyjärvi et al. [30]	waist	7–19	—	36
Rong et al. [34]	waist	6.7	—	35
Rong et al. [33]	waist	5.6, 21.1	—	21
Vildjiounaite et al. [31] (without fusion)	hand	17.2, 14.3	—	31
Vildjiounaite et al. [31] (without fusion)	hip pocket	14.1, 16.8	—	31
Vildjiounaite et al. [31] (without fusion)	breast pocket	14.8, 13.7	—	31

The rest of the paper is structured as follow. Section 2 presents our approach and results on WS-based gait recognition (research question (1)). Section 3 contains security evaluations of gait biometric (research question (2)). Section 4 provides some uniqueness assessment of gait biometric (research question (3)). Section 5 discusses possible application domains and limitations of the WS-based gait recognition. Section 6 concludes the paper.

2. WS-Based Gait Recognition

2.1. Motion Recording Sensor. For collecting gait, we used so called Motion Recording Sensors (MRSs) as shown in Figure 2. The attachment of the MRS to various places on the body is shown in Figure 3. These sensors were designed and developed at Gjøvik University College. The main component of these sensors was an accelerometer which records acceleration of the motion in three orthogonal directions that is up-down, forward-backward, and sideways. From the output of the MRS, we obtained acceleration in terms of $g(g = 9.8 \, \text{m/s}^2)$ (see Figure 5). The sampling frequencies of the accelerometers were $16 \, \text{Hz}$ (first prototype) and $100 \, \text{Hz}$. The other main components of the sensors were a memory for storing acceleration data, communication ports for transferring data, and a battery.

2.2. Recognition Method. We applied various methods to analyze the acceleration signals, which were collected using MRS, from several body segments: foot, hip, trousers pocket, and arm (see Figure 3 for sensor placements). A general structure of our gait recognition methods is visualized in Figure 4. The recognition methods essentially consisted of the following steps.

2.2.1. Preprocessing. In this step, we applied moving average filters to reduce the level of noise in the signals. Then, we computed a resultant acceleration, which is combination of acceleration from three directions of the motion. It was computed as follows:

$$R_i = \sqrt{X_i^2 + Y_i^2 + Z_i^2}, \quad i = 1, \dots, m, \tag{1}$$

where R_i is the resultant acceleration at time i, X_i, Y_i, and Z_i are vertical, forward-backward, and sideway acceleration value at time i, respectively, and m is the number of recorded samples. In most of our analysis, we used resultant acceleration rather than considering 3 signals separately.

2.2.2. Motion Detection. Usually, recorded acceleration signals contained some standing still intervals in the beginning and ending of the signal (Figure 5(a)). Therefore, first we separated the actual walking from the standing still parts. We empirically found that the motion occurs around some specific acceleration value (the value varies for different body locations). We searched for the first such acceleration value and used it as the start of the movement (see Figure 5(a)). A similar procedure could be applied to detect when the motion stops. Thus, the signal between these two points was considered as a walking part and investigated for identity recognition.

2.2.3. Feature Extraction. The feature extraction module analyses motion signals in time or frequency domains. In the time domain, gait cycles (equivalent to two steps) were detected and normalized in time. The normalized cycles were combined to create an average cycle of the person. Then, the averaged cycle was used as a feature vector. Before averaging, some cycles at the beginning and ending of the motion signal were omitted, since the first and last few seconds may not adequately represent the natural gait of the person [35]. An example of selected cycles is given in color in Figure 5(b). In the frequency domain, using Fourier coefficients an amplitude of the acceleration signal is calculated. Then, maximum amplitudes in some frequency ranges are used as a feature vector [37]. We analysed arm signal in frequency domain and the rest of them in time domain.
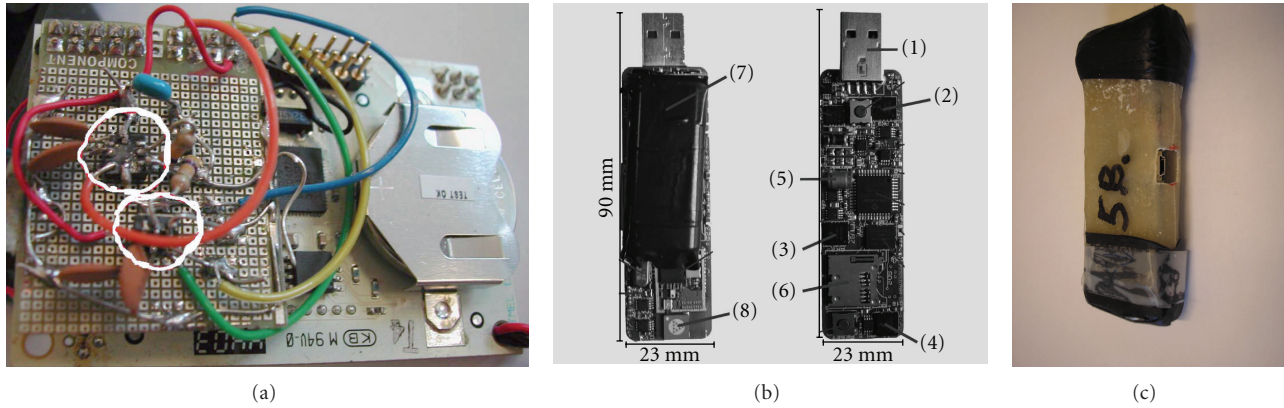
(a)   (b)   (c)

FIGURE 2: Motion recording sensors (MRS).

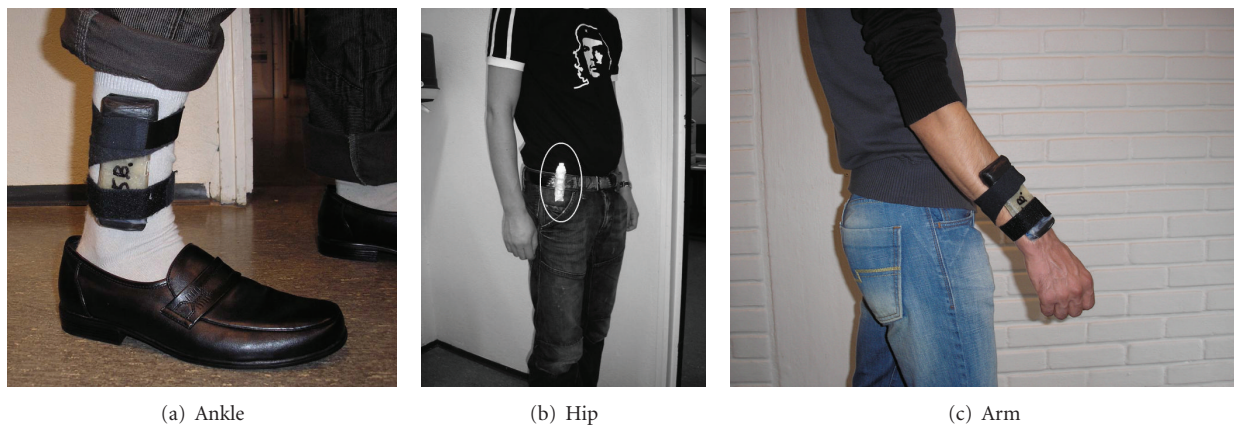(a) Ankle   (b) Hip   (c) Arm

FIGURE 3: The placement of the MRS on the body.

2.2.4. Similarity Computation. For computing similarity score between the template and test samples we applied a distance metric (e.g., Euclidean distance). Then, a decision (i.e., accept or reject) was based on similarity of samples with respect to the specified threshold.

More detailed descriptions of the applied methods on acceleration signals from different body segments can be found in [37–40].

2.3. Experiments and Results. Unlike VS-based gait biometric, no public data-set on WS-based gait is available (perhaps due to the recency of this approach). Therefore, we have conducted four sets of experiments to verify the feasibility of recognizing individuals based on their foot, hip, pocket, and arm motions. The placements of the MRS in those experiments are shown in Figure 3. In case of the pocket experiment, the MRS was put in the trousers pocket of the subjects. All the experiments (foot, hip, pocket, and arm) were conducted separately in an indoor environment. In the experiments, subjects were asked to walk using their natural gait on a level surface. The metadata of the 4 experiments are shown in Table 4. In this table, the column *Experiment* represents the body segment (sensor location) whose motion

was collected. The columns *#S*, *Gender* ($M + F$), *Age range*, *#N*, and *#T* indicate the number of subjects in experiment, the number of male and female subjects, the age range of subjects, the number of gait samples (sequences) per subject, and the total number of gait samples, respectively.

For evaluating performance in verification (one-to-one comparison) and identification (one-to-many comparisons) modes we adopted DET and CMC curves [41], respectively. Although we used several methods (features) on acceleration signals, we only report the best performances for each body segment. The performances of the foot-, hip-, pocket- and arm-based identity recognition in verification and identification modes are given in Figures 6(a) and 6(b), respectively. Performances in terms of the EER and identification rates at rank 1 are also presented in Table 5.

3. Security of Gait Biometric

In spite of many works devoted to the gait biometric, gait security per se (i.e., robustness or vulnerability against attacks) has not received much attention. In many previous works, impostor scores for estimating FAR were generated by matching the normal gait samples of the impostors against

TABLE 4: Summary of experiments.

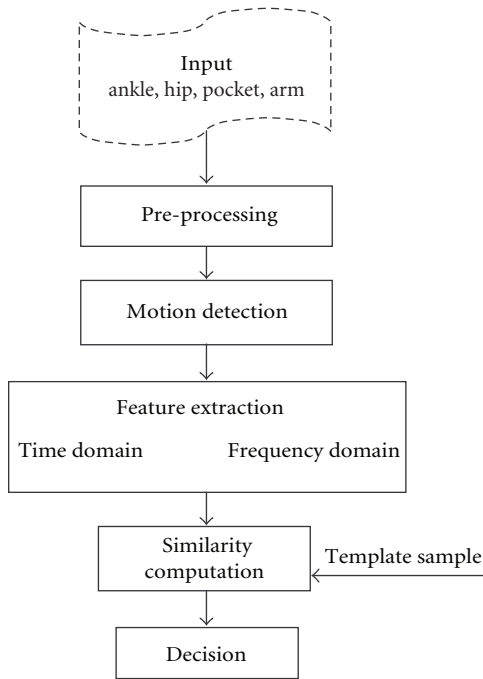| Experiment	#S	Gender (M + F)	Age range	#N	#T
Ankle	21	12 + 9	20–40	2	42
Hip	100	70 + 30	19–62	4	400
Pocket	50	33 + 17	17–62	4	200
Arm	30	23 + 7	19–47	4	120

FIGURE 4: A general structure of recognition methods.

TABLE 5: Summary of performances of our approaches.

MRS placement	Performance, %		#S
	EER	P_1 at rank 1	
Ankle	5	85.7	21
Hip	13	73.2	100
Trousers pocket	7.3	86.3	50
Arm	10	71.7	30

the normal gait samples of the genuine users [15, 17–19, 21, 30]. We will refer to such scenario as a "friendly" testing. However, the "friendly" testing is not adequate for expressing the security strength of gait biometric against motivated attackers, who can perform some action (e.g., mimic) or possess some vulnerability knowledge on the authentication technique.

3.1. Attack Scenarios. In order to assess the robustness of gait biometric in case of hip-based authentication, we tested 3 attack scenarios:

    (1) minimal-effort mimicking [39],

    (2) knowing the closest person in the database [39],

    (3) knowing the gender of users in the database [42].

The minimal-effort mimicking refers to the scenario where the attacker tried to walk as someone else by deliberately changing his walking style. The attacker had limited time and number of attempts to mimic (impersonate) the target person's gait. For estimating FAR, the mimicked gait samples of the attacker were matched against the target person's gait. In the second scenario, we assumed that the attackers knew the identity of person in the database who had the most similar gait to the attacker's gait. For estimating FAR, the attacker's gait was matched only to this nearest person's gait. Afterwards, the performances of mimicking and knowing closest person scenarios were compared to the performance of the "friendly" scenario. In the third scenario, it was assumed that attackers knew the genders of the users in the database. Then, we compared performance of two cases, so called same- and different-gender matching. In the first case, attackers' gait was matched to the same gender users and in the second case attackers' gait was matched to the different gender users. It is worth noting that in second and third attack scenarios, attackers were not mimicking (i.e., their natural gait were matched to the natural gait of the victims) but rather possessed some knowledge about genuine users (their gait and gender).

3.2. Experimental Data and Results. We analyzed the aforementioned security scenarios in case of the hip-based authentication where the MRS was attached to the belt of subjects around hip as in Figure 3(b). For investigating the first attack scenario (i.e., minimal-effort mimicking), we conducted an experiment where 90 subjects participated, 62 male and 28 female. Every subject was paired with another one (45 pairs). The paired subjects were friends, classmates or colleagues (i.e., they knew each other). Everyone was told to study his partner's walking style and try to imitate him or her. One subject from the pair acted as an attacker, the other one as a target, and then the roles were exchanged. The genders of the attacker and the target were the same. In addition, the age and physical characteristics (height and weight) of the attacker and target were not significantly different. All attackers were amateurs and did not have a special training for the purpose of the mimicking. They only studied the target person visually, which can also easily be done in a real-life situation as gait cannot be hidden. The only information about the gait authentication they knew was that the acceleration of normal walking was used. Every attacker made 4 mimicking attempts.

As it was mentioned previously in the second and third attack scenarios (i.e., knowing the closest person and gender of users), the impostors were not mimicking. In these
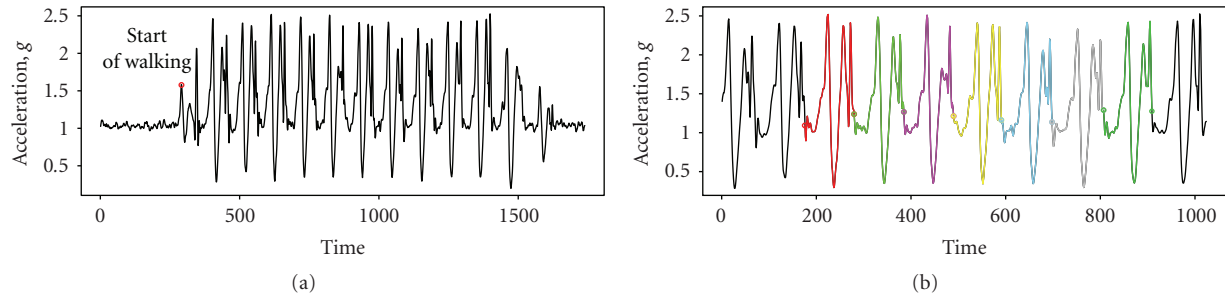
(a)

(b)

FIGURE 5: An example of acceleration signal from foot: (a) motion detection and (b) cycle detection.

(a) Decision error trade-off (DET) cuves

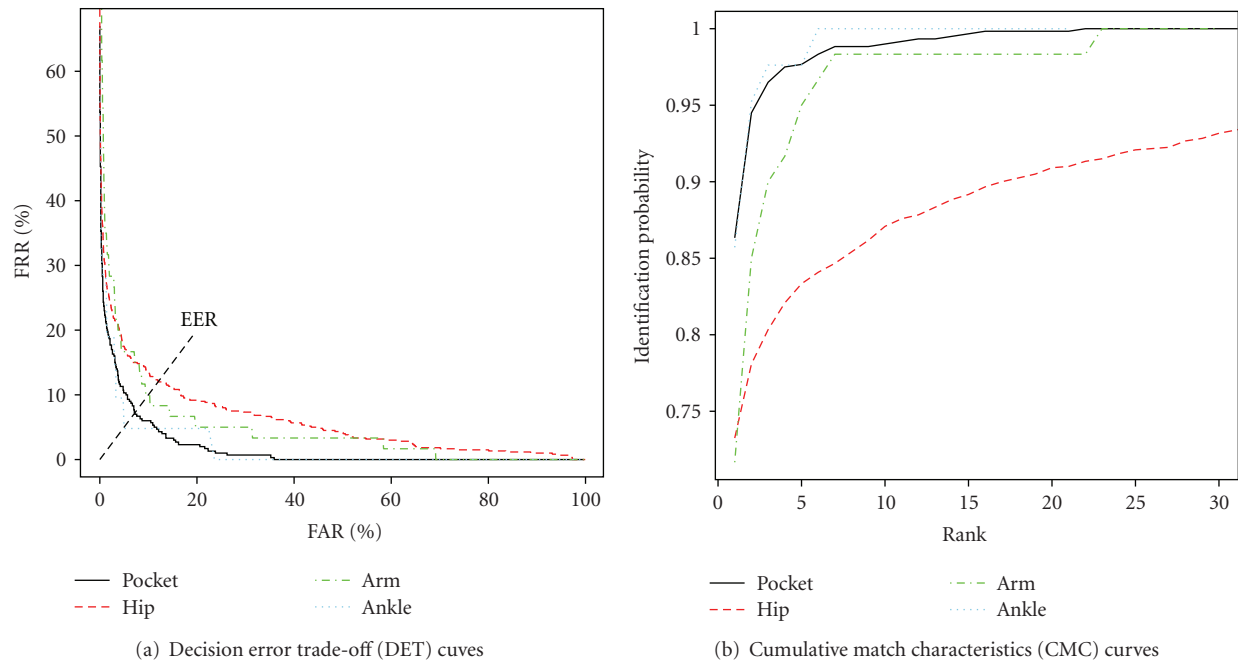(b) Cumulative match characteristics (CMC) curves

FIGURE 6: Performances in terms of DET and CMC curves.

two attack scenarios, the hip data-set from Section 2.3 was used.

In general, the recognition procedure follows the same structure as in Figure 4, and involves preprocessing, motion detection, cycles detection, and computation of the averaged cycle. For calculating a similarity score between two persons' averaged cycle, the Euclidean distance was applied. A more detailed description of the method can be found in [39]. Performance evaluation under attacking scenarios are given in terms of FAR curves (versus threshold) and shown in Figure 7. Figure 7(a) shows the results of the minimal-effort mimicking and knowing the closest person scenarios as well as "friendly" scenario. Figure 7(b) represents the results of security scenario where attackers knew the gender of the victims. In Figures 7(a) and 7(b), the dashed black curve is FRR and its purpose is merely to show the region of EER. In order to get robust picture of comparison, we also computed confidence intervals (CI) for FAR. The CI were computed using nonparametric (subset bootstrap) in Figure 7(a)

and parametric in Figure 7(b) techniques as described in [43].

As can been seen from Figure 7(a), the minimal effort mimicking and "friendly testing" FAR are similar (i.e., black and red curves). This indicates that mimicking does not help to improve the acceptance chances of impostors. However, impostors who know their closest person in the database (green FAR curve) can pose a serious threat to the gait-based user authentication. The FAR curves in Figure 7(b) suggest that impostor attempts, which are matched against the same gender have higher chances of being wrongfully accepted by the system compared to the different sex matching.

4. Uniqueness of Gait Biometric

In the third research question, we investigated some aspects relating or influencing the uniqueness of gait biometric in case of ankle/foot motion [44]. The following three

(a) Friendly testing, mimicking and closest person scenarios
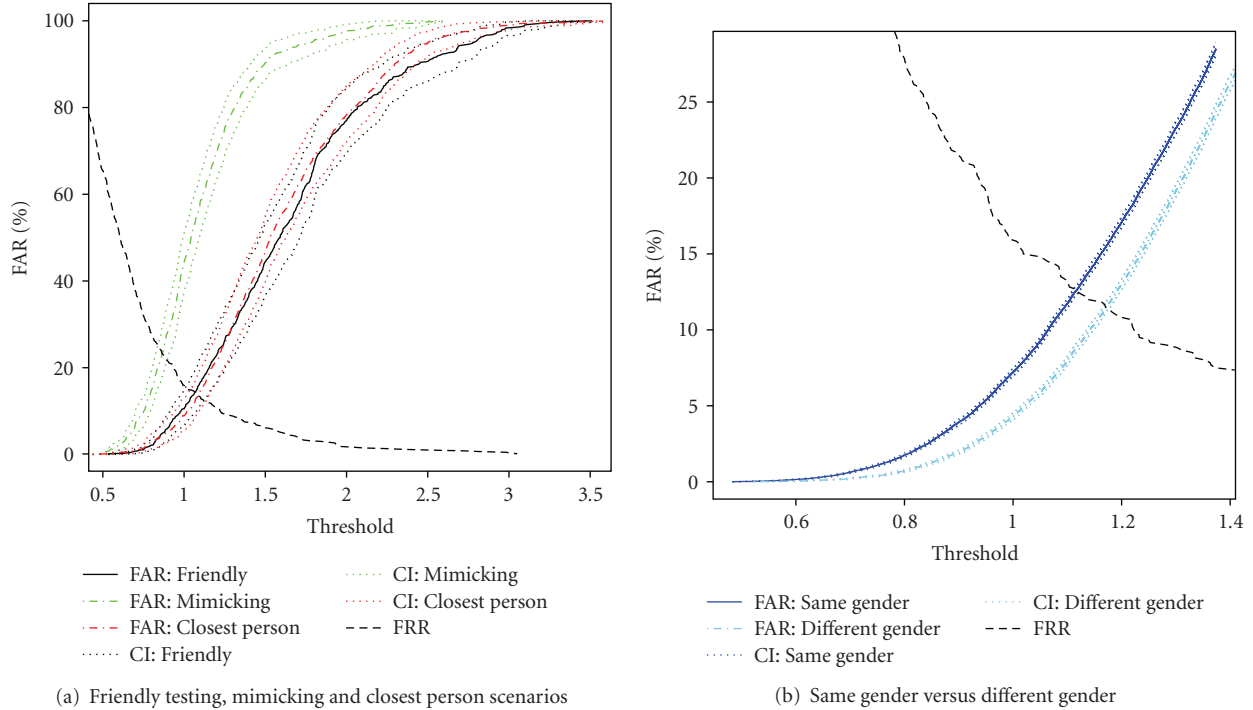
(b) Same gender versus different gender

FIGURE 7: Security assessment in terms of FAR curves.

aspects were studied: footwear characteristics, directions of the motion, and gait cycle parts.

4.1. Experimental Data and Recognition Method. The number of subjects who participated in this experiment was 30. All of them were male, since only men footwears were used. Each subject walked with 4 specific types of footwear, labeled as A, B, C, and D. The photos of these shoe types are given in Figure 8. The footwear types were selected such that people wear them on different occasions. Each subject walked 4 times with every shoe type and the MRS was attached to the ankle as shown in the Figure 3(a). In each of the walking trials, subjects walked using their natural gait for the distance of about 20 m. The number of gait samples per subject was $16 (= 4 \times 4)$ and the total number of walking samples was $480 (= 4 \times 4 \times 30)$.

The gait recognition method applied here follows the architecture depicted in Figure 4. The difference is that in preprocessing stage we did not compute resultant acceleration but rather analyzed the three acceleration signals separately. In the analyses, we used the averaged cycle as a feature vector and applied an ordinary Euclidean distance (except in Section 4.4), see (2), for computing similarity scores

$$s = \sqrt{\sum_{i=1}^{n} (a_i - b_i)^2}, \quad n = 100. \quad (2)$$

In this formula, a_i and b_i are acceleration values in two averaged gait cycles (i.e., test and template). The s is a similarity score between these two gait cycles.

4.2. Footwear Characteristic. Shoe or footwear is an important factor that affects the gait of the person. Studies show that when the test and template gait samples of the person are collected using different shoe types, performance can significantly decrease [45]. In many previous gait recognition experiments, subjects were walking with their own footwear "random footwear." In such settings, a system authenticates *person plus shoe* rather than the *person* per se. In our experimental setting, all participants walked with the same types of footwear which enables to eliminate the noise introduced by the footwear variability. Furthermore, subjects walked with several types of specified footwear. This allows investigating the relationship of the shoe property (e.g., weight) on recognition performance without the effect of "random footwear."

The resulting DET curves with different shoe types in each directions of the motion are given in Figure 9. The EERs of the curves are depicted in the legend of the figures and also presented in Table 6. In this table, the last two columns, FAR and FRR, indicate the EERs' margin of errors (i.e., 95% confidence intervals) for FAR and FRR, respectively. Confidence intervals were computed using parametric approach as in [43].

Although some previous studies reported performance decrease when the test and template samples of the person's walking were obtained using different shoe types [45], there was no attempt to verify any relationship between the shoe attributes and recognition performance. Several characteristics of the footwear can significantly effect gait of the person. One of such attributes is the weight of the shoe. One of the primary physical differences among shoes was in

A   B   C   D

(a)   (b)   (c)   (d)

FIGURE 8: The footwear types A, B, C, and D.

their weight. The shoe types A/B were lighter and smaller than the shoe types C/D. As can be observed from the curves in Figure 9, in general performance is better with the light shoes (i.e., A and B) compared to the heavy shoes (i.e., C and D) in all directions. This suggests that the distinctiveness of gait (i.e., ankle motion) can diminish when wearing heavy footwear.

4.3. Directions of the Motion. Human motion occurs in 3 dimensions (3D): up-down (X), forward-backwards (Y), and sideway (Z). The MRS enables to measure acceleration in 3D. We analyzed performance of each direction of the motion separately to find out which direction provides the most discrimination.

The resulting DET curves for each direction of the motion for every footwear type are given in Figure 10. The EERs of the curves are depicted in the legend of the figures and also presented in Table 6. From Figure 10 one can observe that performance of the sideway acceleration (blue dashed curve) is the best compared to performances of the up-down (black solid curve) or forward-backward (red dotted curve) for all footwear types.

In addition, we also present performance for each direction of the motion regardless of the shoe type. In this case, we conducted comparisons of gait samples by not taking into account with which shoe type it was collected. For example, gait sample with shoe type A was compared to gait samples with shoe types B, C, and D (in addition to other gait samples with shoe type A). These DET curves are depicted in Figure 11 (EERs are also presented in Table 6, last three rows). This figure also clearly indicates that the discriminative performance of the sideway motion is the best compared to the other two.

Algorithms in VS-based gait recognition usually use frontal images of the person, where only up-down and forward-backward motions are available but not the sideway motion. In addition, in some previous WS-based studies [21, 30, 34], authors were focusing only on two directions of the motion: up-down and forward-backward. This is perhaps due to the fact that their accelerometer sensor was attached to the waist (see Figure 1) and there is less sideways movement of the waist compared to the foot. However, our analysis of ankle/foot motion revealed that the sideway direction of the motion provides more discrimination compared to the other two directions of the motion. Interestingly from biomechanical research, Cavanagh [46] also observed that

the runners express their individuality characteristics in medio-lateral (i.e., sideway) shear force.

4.4. Gait Cycle Parts. The natural gait of the person is a periodic process and consists of cycles. Based on the foot motion, a gait cycle can be decomposed into several subevents, such as initial contact, loading response, midstance, initial swing and so on [47]. To investigate how various gait cycle parts contribute to recognition, we introduced a technique for analyzing contribution from each acceleration sample in the gait cycle.

Let the

$$d = \begin{vmatrix} d_{11} & \ldots & d_{1n} \\ d_{21} & \ldots & d_{2n} \\ \ldots & \ldots & \ldots \\ d_{m1} & \ldots & d_{mn} \end{vmatrix},$$

$$\delta = \begin{vmatrix} \delta_{11} & \ldots & \delta_{1n} \\ \delta_{21} & \ldots & \delta_{2n} \\ \ldots & \ldots & \ldots \\ \delta_{k1} & \ldots & \delta_{kn} \end{vmatrix}$$

(3)

be genuine and impostor matrices, respectively, ($m < k$, since usually the number of genuine comparisons is less than number of impostor comparisons). Each row in the matrices is a difference vector between two averaged cycles. For instance, assume $R = r_1, \ldots, r_n$ and $P = p_1, \ldots, p_n$ two feature vectors (i.e., averaged cycles) then values d_{ij} and δ_{ij} in row i in above matrices equal to

(i) $d_{ij} = |r_j - p_j|$, if S and P from the same person (i.e., genuine),

(ii) $\delta_{ij} = |r_j - p_j|$, if S and P from different person (i.e., impostor), where $j = 1, \ldots, n$.

Based on matrices 2 and 3, we define weights w_i as follows:

$$w_i = \frac{\text{Mean}(\delta_{(i)})}{\text{Mean}(d_{(i)})}, \quad (4)$$

where $\text{Mean}(\delta_{(i)})$ and $\text{Mean}(d_{(i)})$ are the means of columns i in matrices δ and d, respectively. Then, instead of the ordinary Euclidean distance as in (2), we used a weighted
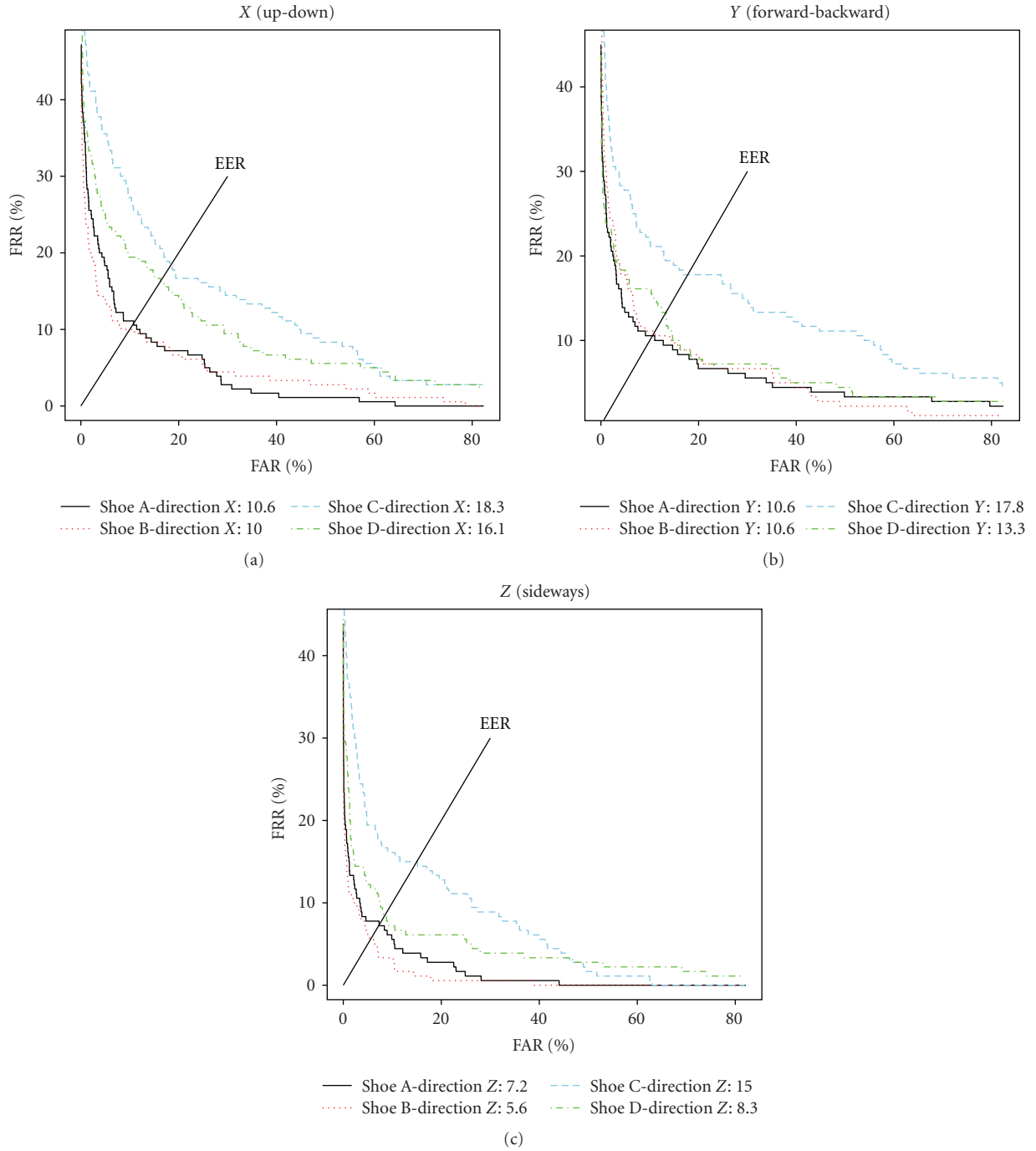
FIGURE 9: Authentication with respect to footwear types for each direction.

version of it as follows:

$$s = \sqrt{\sum_{i=1}^{n}(w_i - 1) * (a_i - b_i)^2}, \quad n = 100, \quad (5)$$

where w_i are from (4). We subtracted 1 from w_i's because if the Mean($\delta_{(i)}$) and Mean($d_{(i)}$) are equal than one can assume that there is no much discriminative information in that particular point.

We used gait samples from one shoe type (type B) to estimate weights and then tested them on gait samples from the other shoe types (i.e., types A, C, and D). The estimated weights are shown in Figure 12. The resulting DET curves are presented in Figure 13 and their EER are also given in Table 7. The DET curves indicate that performance of the weighted approach (red dotted curve) is better than the unweighted one (black solid curve), at least in terms of EER. This is in its turn may suggest that various gait cycle parts (or gait subevents) contribute differently to the recognition.
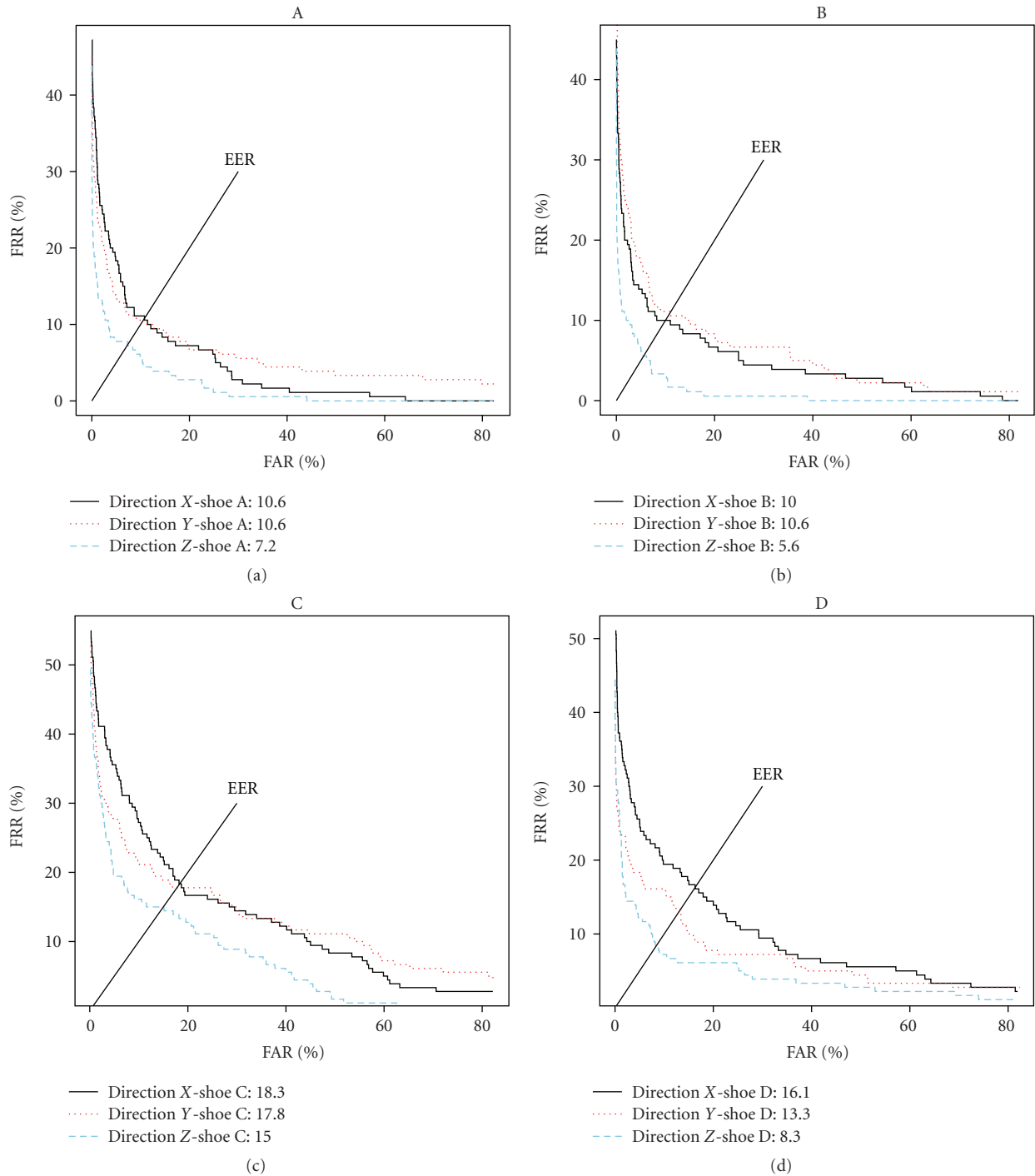
FIGURE 10: Authentication with respect to directions for shoe types A, B, C, and D.

5. Application and Limitation

5.1. Application. A primary advantage of the WS-based gait recognition is on its application domain. Using small, low-power, and low-cost sensors it can enable a periodic (dynamic) reverification of user identity in personal electronics. Unlike one time (static) authentication, periodic reverification can ensure the correct identity of the user all the time by reassuring the (previously authenticated) identity. An important aspect of periodic identity reverification is unobtrusiveness which means not to be annoying, not to distract user attention, and to be user friendly and convenient in frequent use. Consequently, not all authentication methods are unobtrusive and suitable for periodic reverification.

In our experiments, the main reason for selecting places on the body was driven by application perspectives. For

TABLE 6: EERs of the methods. Numbers are given in %.

Shoe type	Motion direction	EER	FAR	FRR
Shoe type A	X (up-down)	10.6	± 0.7	± 4.5
Shoe type B	X (up-down)	10	± 0.7	± 4.4
Shoe type C	X (up-down)	18.3	± 0.9	± 5.6
Shoe type D	X (up-down)	16.1	± 0.9	± 5.4
Shoe type A	Y (forw.-backw.)	10.6	± 0.7	± 4.5
Shoe type B	Y (forw.-backw.)	10.6	± 0.7	± 4.5
Shoe type C	Y (forw.-backw.)	17.8	± 0.9	± 5.6
Shoe type D	Y (forw.-backw.)	13.3	± 0.8	± 5
Shoe type A	Z (sideway)	7.2	± 0.6	± 3.8
Shoe type B	Z (sideway)	5.6	± 0.5	± 3.4
Shoe type C	Z (sideway)	15	± 0.8	± 5.2
Shoe type D	Z (sideway)	8.3	± 0.6	± 4
—	X (up-down)	30.5	± 0.3	± 1.5
—	Y (forw.-backw.)	29.9	± 0.3	± 1.5
—	Z (sideway)	23	± 0.2	± 1.4
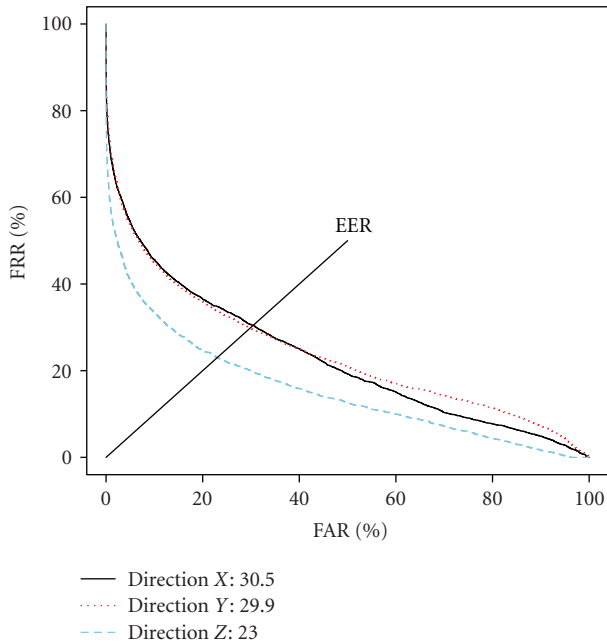
FIGURE 11: Authentication regardless of the shoe types.

Direction X: 30.5
Direction Y: 29.9
Direction Z: 23

FIGURE 12: The estimated weights.

TABLE 7: The unweighted (EER) and weighted distances (EER_w).

Shoe type	Motion direction	EER, %	EER_w, %
Shoe type A	Z (sideway)	7.2	5
Shoe type C	Z (sideway)	15	12.8
Shoe type D	Z (sideway)	8.3	7.8

example, people can carry mobile phone in similar position on the hip or in the pocket. Some models of the mobile phones already equipped with accelerometer sensor, for example, Apple's iPhone [50] has the accelerometer for detecting orientation 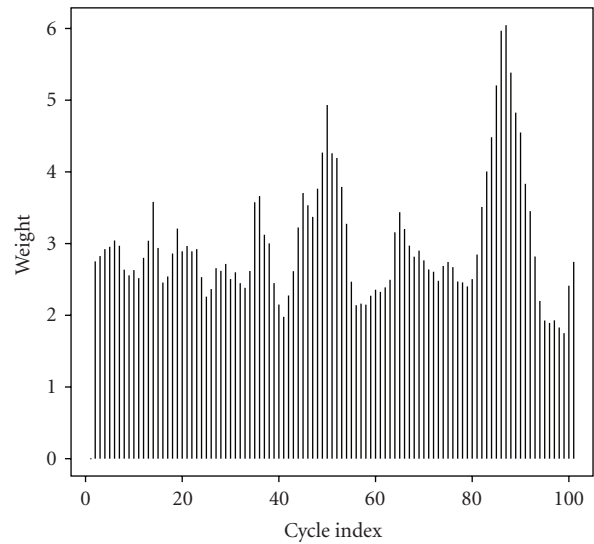of the phone. Nowadays the mobile phone services go beyond mere voice communication, for example, users can store their private data (text, images, videos, etc.) and use it in high security applications such as mobile banking or commerce [51, 52]. All of these increase the risk of being the target of an attack not only because of the phone value per se but also because of the stored information and provided services. User authentication in mobile phones is static, that is, users authenticated once and authentication remains all the time (until the phone explicitly is turned off). In addition, surveys indicate high crimes associated with mobile phones [53] and also suggest that users do not follow the relevant security guidelines, for example, use the same code for multiple services [54].

For combating crimes and improving security in mobile phones, a periodic reverification of the authenticated user is highly desirable. The PIN-based authentication of mobile
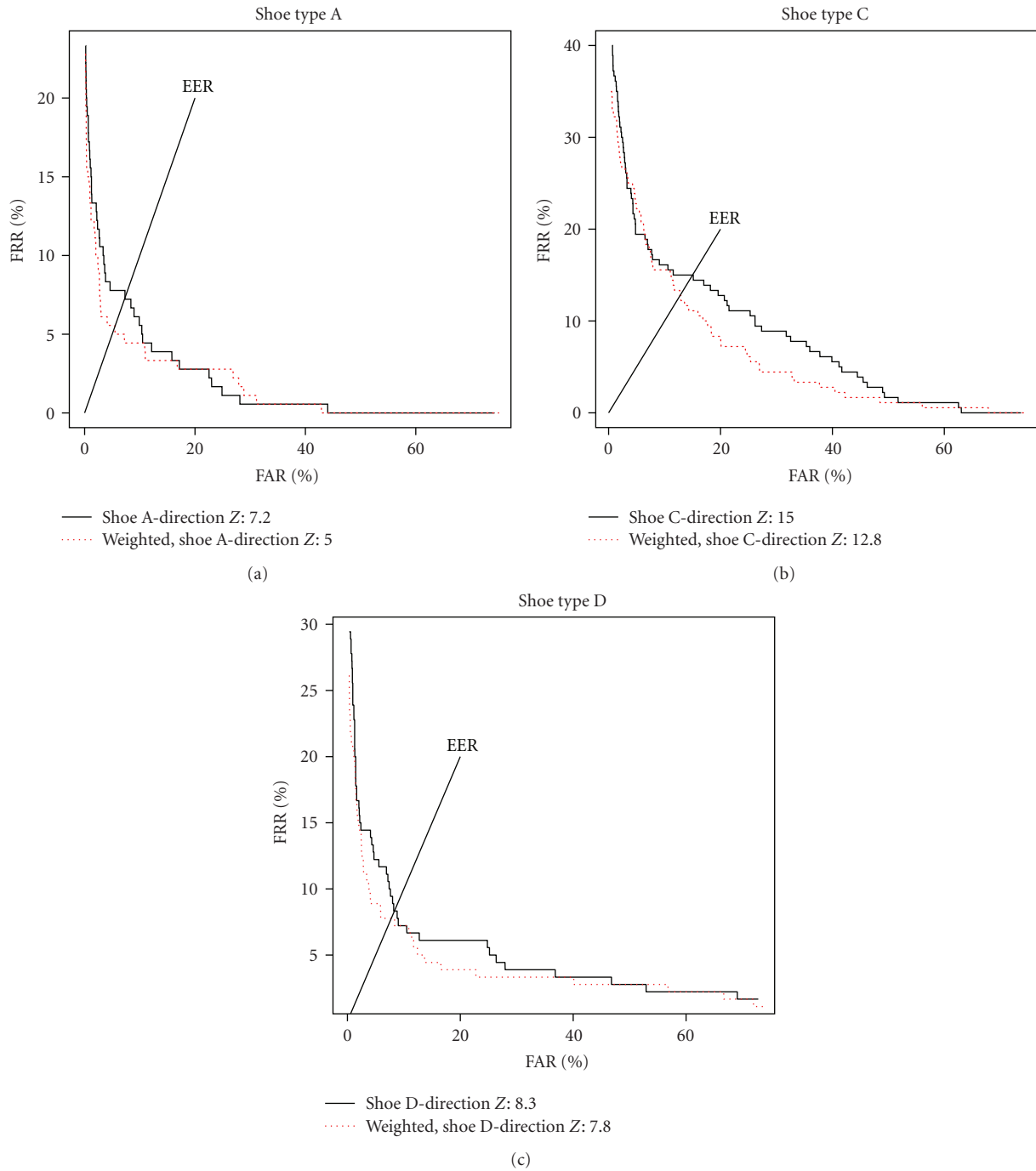
Shoe type A

Shoe type C

Shoe type D

— Shoe A-direction Z: 7.2
..... Weighted, shoe A-direction Z: 5

(a)

— Shoe C-direction Z: 15
..... Weighted, shoe C-direction Z: 12.8

(b)

— Shoe D-direction Z: 8.3
..... Weighted, shoe D-direction Z: 7.8

(c)

FIGURE 13: Ordinary (black) vrsus weighted (red) Euclidean distances.

(a) By Chen et al. [48]
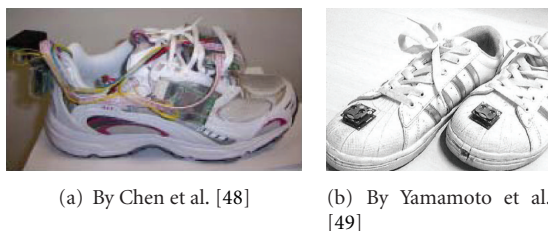
(b) By Yamamoto et al. [49]

FIGURE 14: Examples of smart shoes with integrated accelerometer.

phones is difficult or impossible to adapt for periodic reauthentication because of its obtrusiveness. Indeed, the process of frequently entering the PIN code into a mobile phone is explicit, requires user cooperation, and can be very inconvenient and annoying. Therefore, the WS gait-based analysis can offer better opportunities for periodic identity reverification using MRS embedded in phone hardware or user's clothes (e.g., shoes). Whenever a user makes a few steps his identity is re-verified in a background, without requiring an explicit action or input from the user.

(a) Glove by Sama et al. [55]

(b) Glove by Kim et al. [56]
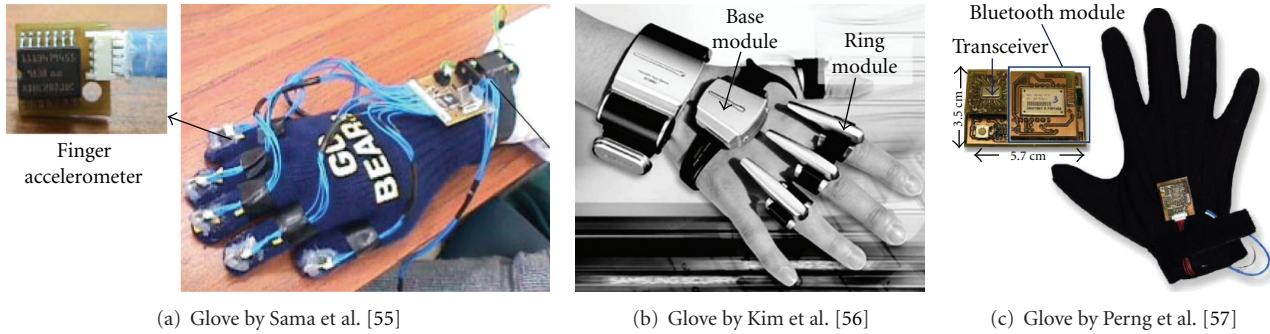
(c) Glove by Perng et al. [57]

FIGURE 15: Examples of the glove like input devices with built-in accelerometer.

Besides the mobile phones and thanks to the rapid miniaturization of electronics, the motion recording/detecting sensors can be found in a wide range of other consumer electronics, gadgets, and clothes. For example,

(i) laptops use accelerometer sensors for drop protection of their hard drive [58];

(ii) various intelligent shoes with integrated sensors are developed (see Figure 14), for example, for detecting abnormal gaits [48], for providing foot motion to the PC as an alternative way of input [49]; Apple and Nike jointly developed a smart shoes that enables the Nike+ footwear to communicate with iPod to provide pedometer functions [59];

(iii) glove like devices with built-in accelerometer (see Figure 15) can detect and translate finger and hand motions as an input to the computer [55–57];

(iv) watches or watch like electronics are equipped with built-in accelerometer sensor [60]. Motion detecting and recording sensors can be built-in even in some exotic applications like tooth brushing [61] or wearable e-textile [62]; and many others.

As the values and services provided by such electronics grow, their risk of being stolen increases as well. Although the motion recording/detecting sensors in the aforementioned products and prototypes are mainly intended for other purposes, it is possible to extend their functionality for periodic re-verification of identity too. Depending on the computing resources, the motion signal can either be analyzed locally (e.g., in case of mobile phones) or remotely in the other surrounding electronics to which data is transferred wirelessly. For instance, a shoe system can transfer the foot motion to the user's computer via wireless network (e.g., Bluetooth).

Furthermore, it is foreseen that such sensors will become a standard feature in many kind of consumer products [63, 64] which implies that WS-based approach will not require an extra hardware. However, it is worth noting that we do not propose the WS-based authentication as a sole or replacement, but rather a complementary one to the traditional authentication techniques (i.e., PIN-code, fingerprint, etc.).

5.2. Limitation. Like the other biometrics, the WS-based gait recognition also possesses its own limitations and challenges. Although the WS-based approach lacks difficulties associated with VS-based approach like noisy background, lighting conditions, and viewing angles, it shares the common factors that influence gait such as walking speed, surface conditions, and foot/leg injuries.

An important challenge related to the WS-based gait recognition includes distinguishing various patterns of walking. Although our methods can differentiate the actual normal walking from the standing still, usually daily activity of an ordinary user involves different types of gait (running, walking fast/slow, walking on stairs up/down, walking with busy hands, etc.). Consequently, advanced techniques are needed for classifying among various complex patterns of daily motion.

The main limitation of the behavioral biometrics including gait is a relatively low performance. Usually, performance of the behavioral biometrics (e.g., voice, handwriting, gait, etc.) is not as accurate as the biometrics like fingerprint or iris. Some ways to improve accuracy can be combining WS-based gait with the other biometrics (e.g., voice [31]), fusing motion from different places (e.g., foot and hip), and/or sensor types (e.g., accelerometer, gyro, etc.). Nevertheless, despite low accuracy of the WS-based gait recognition, it can still be useful as a supplementary method for increasing security by unobtrusive and periodic reverification of the identity. For instance, to reduce inconvenience for a genuine user, one can select a decision threshold where the FRR is low or zero but the FAR is medium to high. In such setting, although the system cannot completely remove impostors of being accepted, it can reduce such risk significantly.

Due to the lack of processing unit in the current prototype of the MRS, our analyses were conducted offline, that is, after walking with MRS, the recorded accelerations were transferred to the computer for processing. However, with computing resources available in some of current electronics we believe it is feasible to analyze motion signals online (i.e., localy) too.

6. Conclusion

In this paper, we presented gait recognition approach which is significantly different from most of current gait biometric research. Our approach was based on analyzing motion signals of the body segments, which were collected by using wearable sensors. Acceleration signals from ankle, hip, trousers pocket, and arm were utilized for person recognition. Analyses of the acceleration signals from these body segments indicated some promising performances. Such gait analysis offers an unobtrusive and periodic (re-)verification of user identity in personal electronics (e.g., mobile phone).

Furthermore, we reported our results on security assessment of gait-based authentication in the case of hip motion. We studied security of the gait-based user authentication under three attack scenarios which were minimal effort-mimicry, knowing the closest person in the database (in terms of gait similarity), and knowing the gender of the user in the database. The findings revealed that the minimal effort mimicking does not help to improve the acceptance chances of impostors. However, impostors who knew their closest person in the database or the gender of the users in the database could pose a threat to the gait-based authentication approach.

In addition, we provided some new insights toward understanding the uniqueness of the gait in case of ankle/foot motion with respect to the shoe attribute, axis of the motion, and gait cycle parts. In particular, our analysis showed that heavy footwear tends to diminish gait's discriminative power and the sideway motion of the foot provides the most discrimination compared to the up-down or forward-backward direction of the motion. Our analysis also revealed that various gait cycle parts (i.e., subevents) contribute differently toward recognition performance.

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