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User authentication based on foot motion

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Abstract In nearly all current systems, user authentication mechanism is one time and static. Although such type of user authentication is sufficient for many types of applications, in some scenarios, continuous or periodic re-verification of the identity is desirable, especially in high-security application. In this paper, we study user authentication based on 3D foot motion, which can be suitable for periodic identity re-verification purposes. Three-directional (3D) motion of the foot (in terms of acceleration signals) is collected using a wearable accelerometer sensor attached to the ankle of the person. Ankle accelerations from three directions (up-down, forward-backward and sideways) are analyzed for person authentication. Applied recognition method is based on detecting individual cycles in the signal and then finding best matching cycle pair between two acceleration signals. Using experimental data from 30 subjects, obtained EERs (Equal Error Rates) were in the range of 1.6–23.7% depending on motion directions and shoe types. Furthermore, by combining acceleration signals from 2D and 3D and then applying fusing techniques, recognition accuracies could be improved even further. The achieved performance improvements (in terms of EER) were up to 68.8%.

Keywords User authentication · Biometrics · Gait recognition · Acceleration signal · Foot motion · Wearable sensor

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1 Introduction

Most of current user authentication mechanisms are one time and static. In other words, once individual's identity is verified (e.g., by providing a correct PIN code or presenting a fingerprint), this lasts forever unless the user explicitly terminates session. Usually, explicit termination of the session is not performed or not of interest. Such kind of user authentication is sufficient for many cases. However, in some scenarios, *continuous* or *periodic re-verification* of the identity is highly desirable, especially in high-security application. For example, nowadays services provided by mobile phones go beyond mere audio communications, and they can be used in mobile payment applications [1,2] and can also contain private and personal data (images, videos, schedules, etc.). On the one hand, mobile phones are not always under the attention of their owners, e.g., some people tend to forget, leave unattended or even lose them. On the other hand, due to increased services of the devices, the associated risks of being target of an attack also increases (e.g., a crime survey reported that about 800.000 owners experienced theft [3]). Since user authentication in mobile phones is one time and static, an impostor who obtains phone in turned-on state can easily explore it. Consequently, in order to prevent (or at least minimize) unauthorized access to the mobile devices, a periodic authentication of the owner is desirable to ensure the correct identity of the user throughout usage. An important requirement of periodic authentication is to be unobtrusive and convenient. Therefore, traditional PIN-based authentication in mobile phones is difficult or impossible to adapt for periodic re-authentication because it is obtrusive, requires explicit action from the user side and can be very annoying in frequent use.

A natural daily activity of the person that does not require an explicit action, for example walking, can be a good candidate for periodic re-verification. Recognizing people based on their walking style is referred as a gait recognition [4]. From technological perspective, approaches in gait recognition can be categorized into three classes [5]:

- video sensor (VS) based,
- floor sensor (FS) based and
- 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 various gait features for recognition [6,7]. A significant amount of research in the area of gait recognition is focused on VS-based gait recognition [4]. One reason for much interest in VS-based gait category can be also attributed to the availability of large public gait databases that are provided by academic institutes [8–10]. In the FS-based approach, sensors are installed in the floor and different gait-related data (e.g., Ground Reaction Force) are measured when people walk on them [11]. In WS-based approach, so-called motion recording sensors are worn or attached to various places on the body of the person such as shoe, waist and so on [12,13]. Then, a movement signal (e.g., in terms of acceleration) recorded by such sensors is utilized for person recognition purposes.

Among the three approaches, the WS-based gait recognition is the most recent one. To the best of our knowledge, the first work using wearable sensors for recognizing individuals was reported by [12], although their primary focus was not on identity recognition. The first work of using WS-based approach with the primary focus on identity verification is the work by Ailisto et al. [13].

In this paper, we describe a WS-based gait recognition approach that can be suitable for periodic identity verification. The contribution of the paper is not algorithmic in nature, rather investigation and analyses of different aspects in identity verification based on foot. In particular, the main contribution of this work and its distinctive characteristics are as follows:

- Unlike almost all previous studies in the experimental setting of this work, the influence of footwear is minimized since all subjects walk with the same type of footwear.
- Foot acceleration signals are analyzed with respect to the direction of the motion (i.e., up-down, forward-backward and sideways) and shoe type (e.g., light and heavy).
- Various fusion combinations of the acceleration signals are explored for possible improvement in the performance accuracy.

The rest of the paper is structured as follow. The Sect. 2 presents an performance overview of several previous works on person recognition based on foot and its possible application area. Sections 3 and 4 describe data collection and applied gait recognition method, respectively. The Sect. 5 reports evaluation results both without and with fusion. Section 6 draws some conclusion and points out to potential directions for future work.

2 Previous works and application

Most gait recognition methods are based on the whole-body movement not merely foot motion. However, this section focuses on studies that is mainly involves foot. Table 1 present a short performance summary of several FS-based and WS-based person recognition studies that are based on feet. In this table, second and third columns represent achieved performance(s) and number of subjects in experiments, respectively. In the table, performance accuracies are given in terms of recognition rate (first nine rows—i.e., studies [11,12,14–20]) and also in terms of EER (Equal Error Rate) and/or FRR (False Reject Rate) at the specified FAR (False Accept Rate) (the last six rows i.e., studies [21–24] and this paper). It is worth noting that a direct comparison of performances from this table may not be adequate because of difference among the data sets. The purpose of this table is to give an overview of performances in this area (and not comparison of performances). Although performances are promising in this table, in most works, the number of subjects in experiments are limited and not more than 15 (except [20] and [21]). Number of participants in our experiments is relatively larger compared to most of the works in Table 1.

WS-based gait recognition provides means of enhancing user authentication security by continuous or periodic

Table 1 Summary of person recognition works based on foot

Study	Performance, %	#S
Orr and Abowd [11]	93	15
Morris [12]	97.4	10
Huang et al. [14]	96.93	9
Nakajima et al. [15]	85	10
Suutala and Röning [16]	65.8–70.2	11
Suutala and Röning [17]	79.2–98.2	11
Suutala and Röning [18]	92	10
Middleton et al. [19]	80	15
Jenkins and Ellis [20]	39	62
Takeda [21]	FRR = 13.9 at FAR = 0.48; EER = 6.1	30
Ye et al. [22]	FRR = 12 at FAR = 1	11
Yamakawa et al. [23]	FRR = 6.9 at FAR = 0.02	10
Mostayed et al. [24]	FRR = 16 at FAR = 3.33	–
This paper (without fusion)	EER range = {1.6–23.7}	30
This paper (with fusion)	EER range = {0.5–19.22}	30

(a) Chen et al. [25]. (b) Kong et al. [26]. (c) Kit by Nike and Apple [29]. (d) Yamamoto et al. [27]. (e) Xe et al. [28].

Fig. 1 Examples of smart shoes with integrated sensors

re-verification of identity. One possible application for the foot-based person verification using WS-based approach can be intelligent footwear that is able to provide identity information based on its owner's walking. In such system, hardware component for recording foot motion is integrated with shoes per se. Already various shoes equipped with intelligent sensors have been proposed and developed, see Fig. 1. For instance, for detecting abnormal gaits [25,26], for providing foot motion to the PC as an alternative way of input [27,28], Apple and Nike jointly developed a smart shoe that enables the Nike+ footwear to communicate with iPod to provide pedometer functions [29].

Although the motion recording and detecting sensors in the aforementioned shoes were mainly intended for other purposes, it is possible to extend their functionality for periodic re-verification of identity too. Furthermore, this can be realized by merely adding appropriate software component to the system without any extra hardware component. When users walk, his or hers shoe can provide owner's identity to the surrounding electronics or systems (e.g., mobile phone, computer) via wireless communication (e.g., Bluetooth). In other words, 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. It is also foreseen that such motion detecting and recording sensors will become standard feature in many other future gadgets [30]. In addition, it has been shown that motion from other parts of body like waist [13], hip [31], pocket [32] and arm [33] can also be used for user authentication.

(a) shoe type A (b) shoe type B (c) shoe type C (d) shoe type D

Fig. 2 The four footwear types

3 Gait data set

Unlike VS-based gait studies, to the best of our knowledge so far, no public gait data set, which is collected using wearable sensor, is available. Therefore, first, we created a data set of foot motions using a so-called motion recording sensor (MRS). In addition to the accelerometer, the other main components of the MRS include an internal memory of 64 MB for storing acceleration values and a re-chargeable battery. Sampling frequency of the accelerometer sensor was $f_s = 100$ Hz.

Fig. 3 The MRS attachment to the ankle

The MRS was attached to the ankle of the subjects as shown in Fig. 3. The sensor recorded accelerations in three orthogonal directions (3D), up-down (X), forward-backward (Y) and sideways (Z). In the rest of the paper, we will refer to these three directions as X, Y and Z, respectively. The recording of acceleration signals from these directions is synchronized.

In nearly all previous gait experiments, participants walked with their own shoe type. In such cases, the applied methods perform recognition of "person+shoe" rather than a "person per se". A distinctive characteristics of our experiments (and consequently gait data set) is that all subjects walked with the same types of footwear. Each subject walked using specified four kinds of footwear. The footwears are labeled as A, B, C and D, and their photographs are shown in Fig. 2. For each shoe type, we provided three sizes (41, 42 and 43—EU standard) such that participants can choose their suitable sizes.[1] During walking, the MRS was attached to the ankle as shown in the Fig. 3. In every walking trial, subjects walked using their natural gait for the distance of about 20 m. When the walking was completed, the collected data were transferred to the PC for analysis. Each subject had 4 walking trials with every shoe type. Thirty persons had participated in the experiment. The number of walking sequences (or samples) per subject was 16 (4×4), and the total number of walking samples was 480.

4 Recognition method

The gait recognition method consists of the following steps:

1. *Pre-processing* The raw signals produced by the sensor were transformed to obtain them in units of gravity, $g(g = 9.8\,\mathrm{m/s}^2)$. Then, we apply a weighted moving average filter to reduce the level of noise in acceleration signals.
2. *Detecting Motion* Each acceleration signal contains standing still parts at the start and end of the signal. Such parts of the acceleration signal correspond to more or less flat signal. In other words, subjects were told to stand still for few seconds before and after walking sessions. These parts were introduced because usually gait starts from standing still, and the recognition algorithm should be able to differentiate gait motion from no motion. We detect the start of motion from the up-down acceleration. Empirical observations indicate that the motion occurs at around $g_0 = 1.55$. We search for the first acceleration value, which is greater than g_0 and decide this point as the start of the movement (see Fig. 4a). A similar procedure can be applied to detect when the motion stops. Figure 4a shows an example of acceleration signal with a detected start of motion. The same starting and ending positions are also applied for signals from forward-backward and sideways directions since the recording is synchronized.
3. *Detecting Cycles* After the motion part of the signal is identified, we search for individual cycles in this part. Again, we use up-down acceleration signal to identify start and end points of the cycles. Then decide the same time points in the other two directions as well because the recording of acceleration in three directions is synchronized. If the sequence of acceleration values fall between the two threshold values ($T_{\min}$ and $T_{\max}$) for a given duration (T_{dur}), then this sequence is decided as a stance phase of gait cycle. Then, from the start of one stance phase until the start of the next stance phase is considered as one cycle. Assume $F = < f_1, f_2, \ldots, f_n >$ is the up-down ankle motion signal. The $F_{ij} = < f_i, f_{i+1}, \ldots, f_j >$ denotes the subsequence of the F. From F, we identify all max duration subsequences F_{ij} that satisfy the following conditions:
$$(f_k < T_{\max}) \quad \text{and} \quad (f_k > T_{\min}) \quad \text{and} \quad (j - i < T_{\text{dur}}). \quad (1)$$
Such subsequences F_{ij} are considered as stance phases. The values for $T_{\min}$, $T_{\max}$ and T_{dur} are estimated based on sampling frequency of sensor and information about natural walking speed of the person.
After cycles are identified, we omit few cycles in the beginning and ending, since the starting and ending steps may not adequately represent the natural gait of the person [34]. An example of detected cycles is shown in color in Fig. 4b. We normalize (by interpolation) the detected cycles in time such that each cycle consists of exactly 100 ($= f_s$) acceleration value.
4. *Comparing Cycles* Previously, we used an average cycle as a feature vector, which was computed by combining normalized cycles into one [35]. In this work, we do not compute an average cycle but rather conduct cross-comparison between two sets of cycles to find the best matching cycle pair. Assume two sets of normalized cycles are $C^E = \{C_1^E, \ldots, C_M^E\}$ and

[1] Therefore, only people having one of these footwear sizes were invited to participate in the experiments.

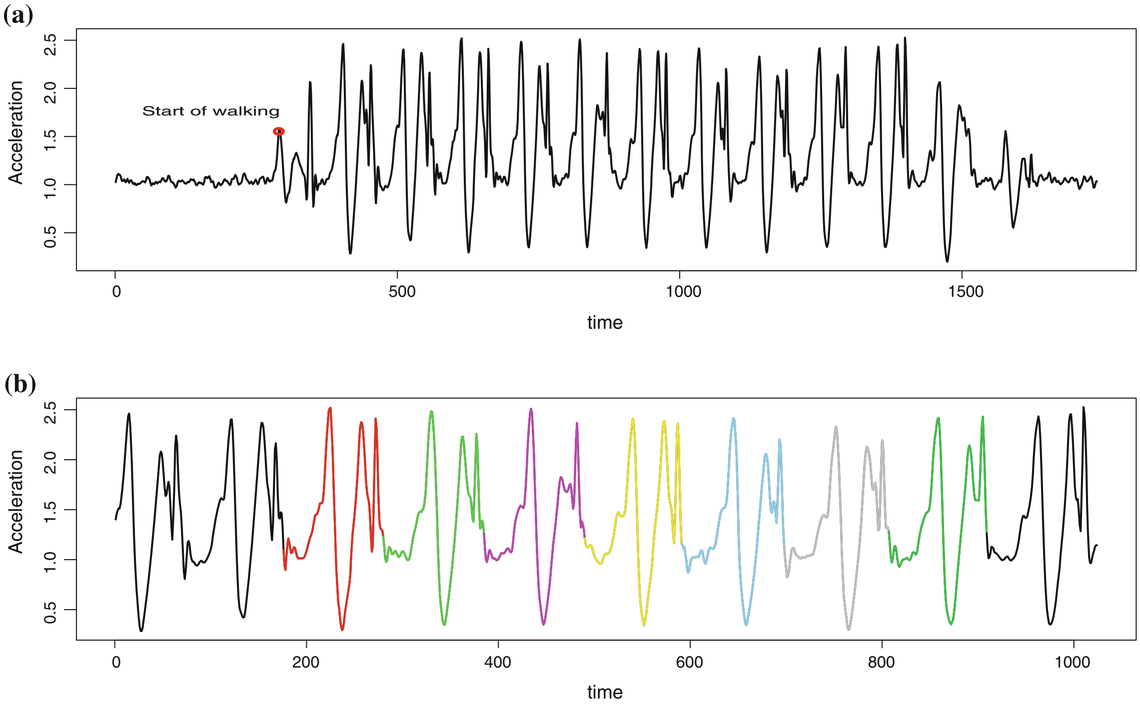

Fig. 4 Acceleration example: **a** detected start of motion and **b** detected cycles (in *color*)

$C^F = \{C_1^F, \ldots, C_N^F\}$. These sets can be from the same (genuine matching) or different (impostor matching) subjects. We compare each cycle from the set C^E to every cycle in set C^F and calculate their similarity using Euclidean distance as follow.

$$\text{Score}\left(C_k^E, C_p^F\right) = \sqrt{\sum_{i=1}^{100}\left(C_{k(i)}^E - C_{p(i)}^F\right)^2} \quad (2)$$

where $1 \leq k \leq M$, $1 \leq p \leq N$; C_k^E is the cycle k from the set C^E and C_p^F is the cycle p from the set C^F; and each element, $C_{k(i)}^E$ and $C_{p(i)}^F$, represent the up-down value from the accelerometer. From the total number of $N \cdot M$ comparison scores, we select a minimum one, i.e., $s_{\min} = \min\{\text{Score}(C_k^E, C_p^F)\}$. The pair of cycles that produced the minimum comparison score is considered as a best matching cycles. Then, this best (i.e., minimum) score, $s_{\min}$, is considered as the comparison (or also referred as a similarity) score between sets C^E and C^F.
Similarly, for acceleration signals from forward-backward and sideways directions, the same cycle position is used, and Eq. 2 is also applied to compute the corresponding comparison score $s_{\min}$.

5. *Decision*: Finally, a decision of either *accept* or *reject* is conducted using comparison score with respect to some threshold value. If the comparison score is equal or smaller than the threshold, then *accept* otherwise *reject*.

5 Results and discussion

To evaluate performance, we use a DET (Decision Error Trade-off) curve, which is a plot of FAR (False Accept Rate) versus FRR (False Reject Rate). The DET curve shows the performance of a biometric system under different decision thresholds. Usually, to indicate performance of the system by a single value, an Equal Error Rate (EER) is used. The EER is a point in the DET curve where FAR = FRR.

We denote gait samples from shoe types A, B, C and D as S_A, S_B, S_C and S_D, respectively. Then, we define sets $S_{\text{light}} = S_A \cup S_B$, $S_{\text{heavy}} = S_C \cup S_D$ and $S_{\text{all}} = S_A \cup S_B \cup S_C \cup S_D$ as samples from the light shoes (i.e., A and B), samples from the heavy shoes (i.e., C and D) and samples from all shoes (i.e., A, B, C and D), respectively.

5.1 Results without fusion

The resulting DET curves with different shoe types (i.e., sets S_A, S_B, S_C and S_D separately) are given in Fig. 5 for each direction of motion separately. The EERs of the curves are depicted in the legend of the figures and also presented in Table 2. In this table, in the last column, the EERs of our previous recognition method [35] on the same gait data set are also shown.

One of the main differences between footwear types A/B and C/D was in their weights. From the curves in Fig. 5, one can observe that performance is better with the light shoes

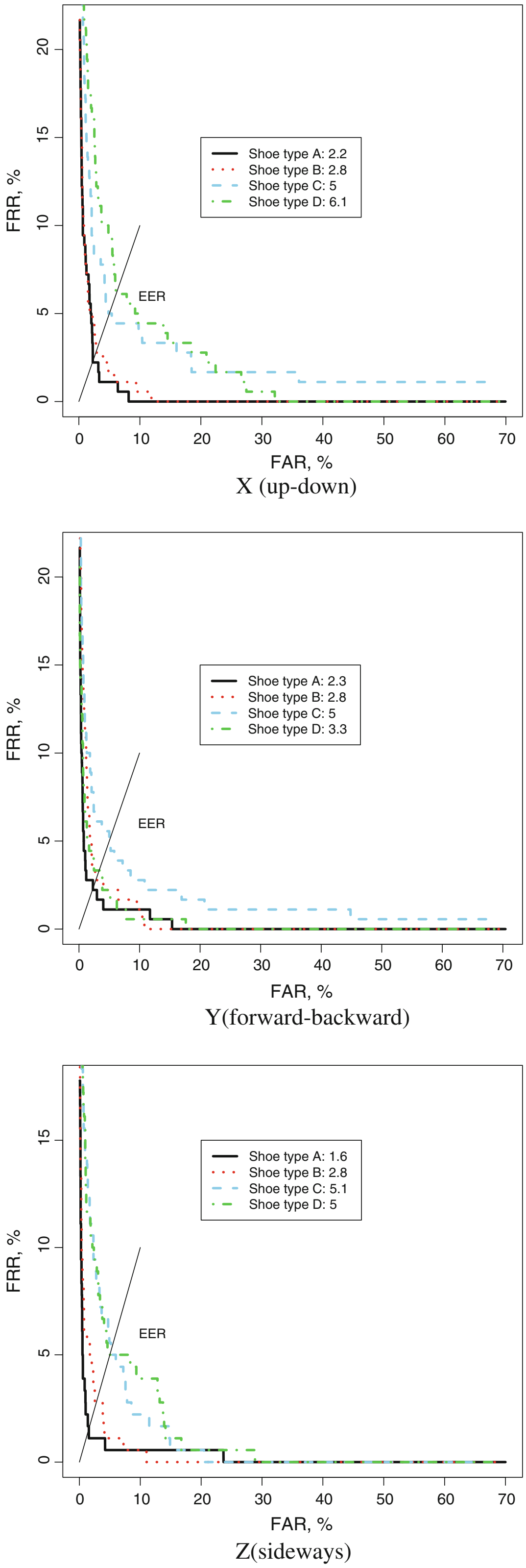

Fig. 5 Authentication with respect to footwear types for each direction

Table 2 EERs of the methods

Shoe type	Motion direction	EER	Prev. EER [35]
Shoe type A	X (up-down)	2.2	10.6
Shoe type A	Y (forw.-backw.)	2.3	10.6
Shoe type A	Z (sideway)	1.6	7.2
Shoe type B	X (up-down)	2.8	10
Shoe type B	Y (forw.-backw.)	2.8	10.6
Shoe type B	Z (sideway)	2.8	5.6
Shoe type C	X (up-down)	5	18.3
Shoe type C	Y (forw.-backw.)	5	17.8
Shoe type C	Z (sideway)	5.1	15
Shoe type D	X (up-down)	6.1	16.1
Shoe type D	Y (forw.-backw.)	3.3	13.3
Shoe type D	Z (sideway)	5	8.3
Light shoes (A and B)	X (up-down)	11.4	–
Light shoes (A and B)	Y (forw.-backw.)	13.4	–
Light shoes (A and B)	Z (sideway)	9.8	–
Heavy shoes (C and D)	X (up-down)	23.7	–
Heavy shoes (C and D)	Y (forw.-backw.)	17	–
Heavy shoes (C and D)	Z (sideway)	16.2	–
All shoes	X (up-down)	23.6	30.5
All shoes	Y (forw.-backw.)	21.4	29.9
All shoes	Z (sideway)	16.4	23

Numbers are given in %

(i.e., A and B) compared to the heavy shoes (i.e., C and D), especially in up-down (X) and sideways (Z) directions.

We also present a general authentication performance for each direction of motion with respect to the light shoes (i.e., S_{light}), heavy shoes (i.e., S_{heavy}) and all shoe type (i.e., S_{all}). The estimated DET curves are depicted in Fig. 6 (EERs are also presented in Table 2). The DET curves in the figure indicate that the discriminative performance of the sideway motion is better compared to the performances of up-down or forward-backward.

5.2 Results with fusion

Although performances (based on separate directions) appear to be encouraging especially with sideways motion of the foot, we studied possibility of further improvement using a fusion technique by combining information from 2D and 3D. The fusion is conducted at the score level, and the following four possible combinations of the movement directions were investigated:

1. X (up-down) and Y (forw.-backw.), referred as XY
2. X (up-down) and Z (sideway), referred as XZ
3. Y (forw.-backw.) and Z (sideway), referred as YZ
4. X (up-down), Y (forw.-backw.) and Z (sideway), referred as XYZ

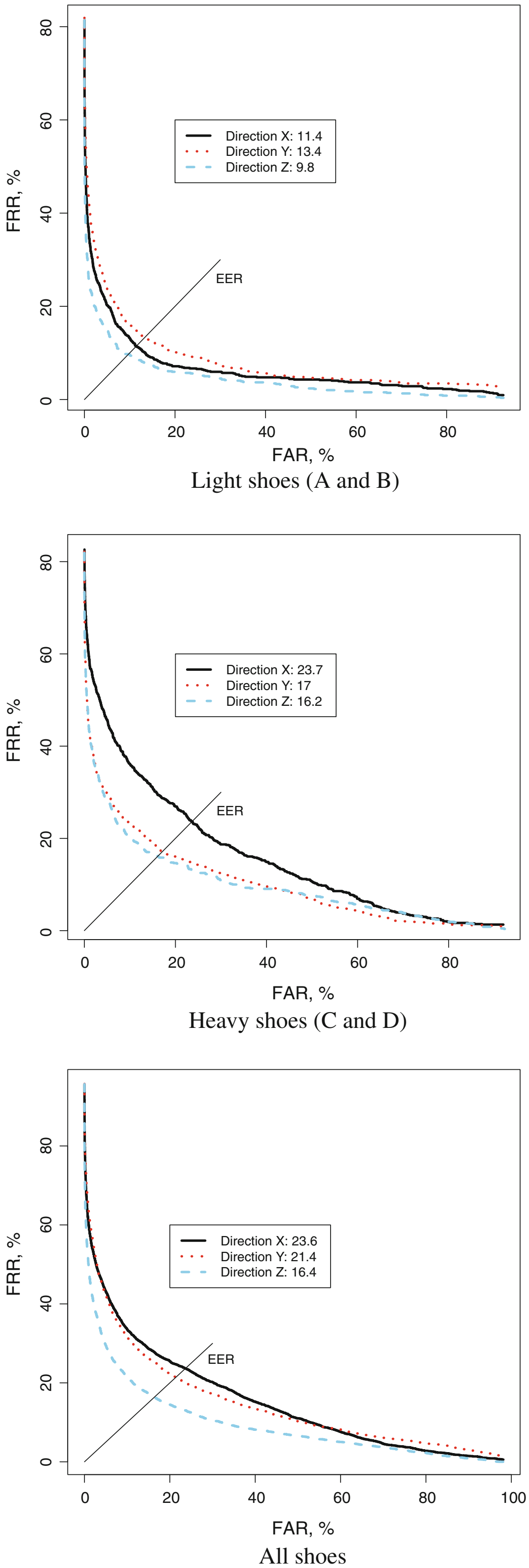

Fig. 6 Performance regardless of shoe type

For fusion, we applied a weighted sum rule where fused similarity score is computed using Eq. 3

$$S_{\text{fusion}} = w_X * s_X + w_Y * s_Y + w_Z * s_Z \tag{3}$$

where in this equation, s_i, w_i and S_{fusion} are similarity scores from the direction $i(i = X, Y, Z)$, their corresponding weight values and a resulting fused score, respectively. The weights are selected such that to satisfy condition $w_X + w_Y + w_Z = 1$. Previously, in other biometric studies, computing weights based on EER values of individual modalities shown to be useful [36,37]. For the four aforementioned combinations, weights were also computed using EER values as follow

1. For *XY* combination:

$$w_X = \frac{\text{EER}_Y}{\text{EER}_X + \text{EER}_Y}$$
$$w_Y = \frac{\text{EER}_X}{\text{EER}_X + \text{EER}_Y}$$
$$w_Z = 0$$

2. For *XZ* combination:

$$w_X = \frac{\text{EER}_Z}{\text{EER}_X + \text{EER}_Z}$$
$$w_Z = \frac{\text{EER}_X}{\text{EER}_X + \text{EER}_Z}$$
$$w_Y = 0$$

3. For *YZ* combination:

$$w_Z = \frac{\text{EER}_Y}{\text{EER}_Z + \text{EER}_Y}$$
$$w_Y = \frac{\text{EER}_Z}{\text{EER}_Z + \text{EER}_Y}$$
$$w_X = 0$$

4. For *XYZ* combination:

$$w_X = \frac{\text{EER}_Y + \text{EER}_Z}{2 * (\text{EER}_X + \text{EER}_Y + \text{EER}_Z)}$$
$$w_Y = \frac{\text{EER}_X + \text{EER}_Z}{2 * (\text{EER}_X + \text{EER}_Y + \text{EER}_Z)}$$
$$w_Z = \frac{\text{EER}_X + \text{EER}_Y}{2 * (\text{EER}_X + \text{EER}_Y + \text{EER}_Z)}$$

where w_i and EER_i are corresponding weights and the EER value for direction $i(i = X, Y, Z)$ in a specified combination.

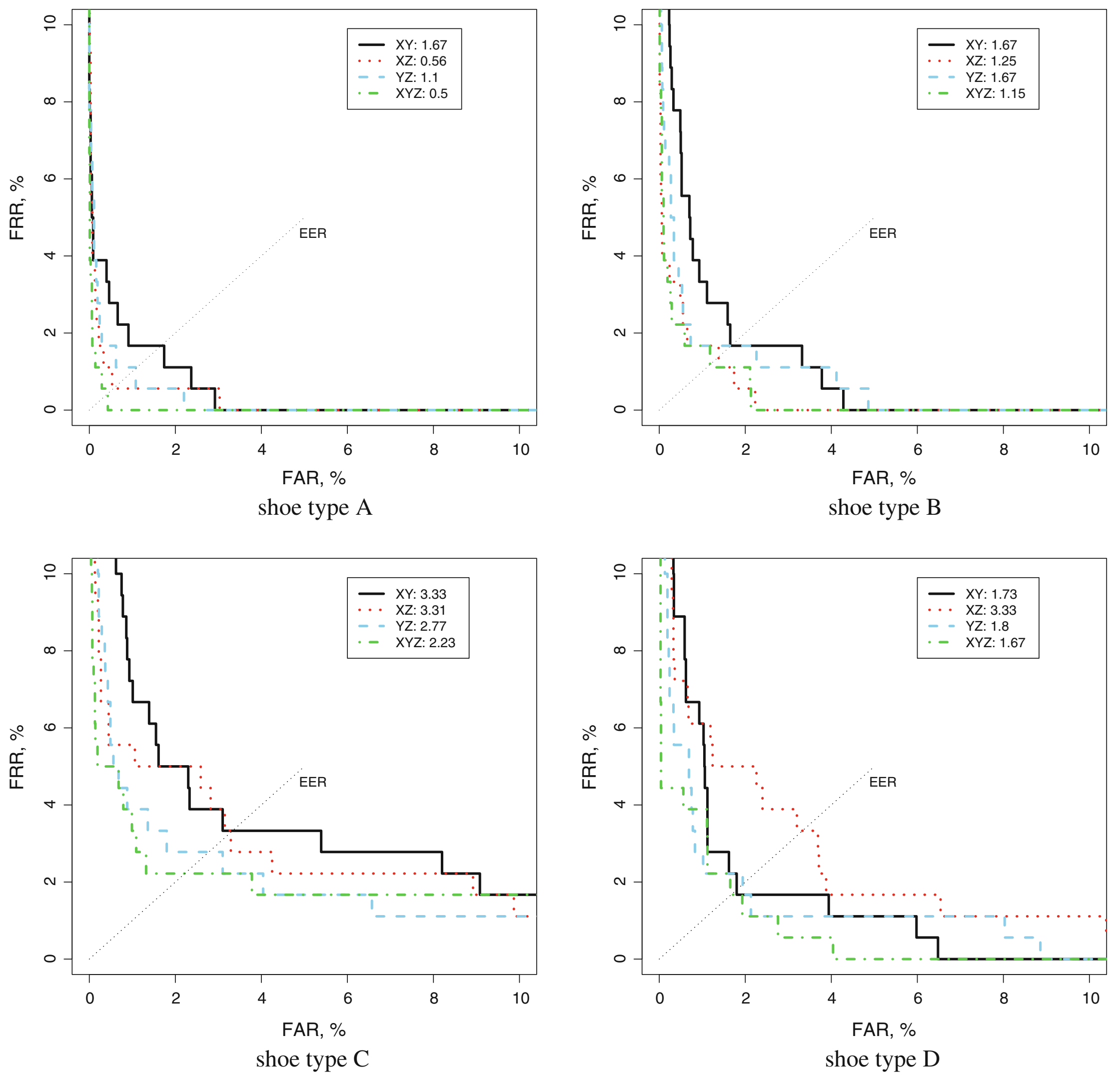

Fig. 7 Fusion performance for each shoe type

For estimating weights, we set $\text{EER}_X = 2.2, \text{EER}_Y = 2.3$ and $\text{EER}_Z = 1.6$ (values from shoe type A see Table 2).

The performance curves using fusion for four shoes types are presented in Fig. 7 and similarly for light, heavy and all shoe are shown in Fig. 8. Table 3 shows a best EER without fusion (from Table 2) and EER of the fused methods. We also define performance improvement (in terms of EER), Δ_{ij}, between methods i and j according to Eq. 4.

$$\Delta_{ij} = \frac{\text{EER}_i - \text{EER}_j}{\text{EER}_i} \cdot 100\% \tag{4}$$

In Table 3, last column presents improvements (using Eq. 4) between best EER without fusion and EER with fusion (using *XYZ* combination), which are in range of 0–68.8%.

5.3 Discussion

The primary motivation to use foot motion for identity verification is driven by the fact that feet are the main body parts during locomotion.

An interesting fact to observe from this study is that the performance of the sideways motion being better compared to the performances of up-down or forward-backward direction of the motion, e.g., see Fig. 6. Although acceleration of the feet can be obtained from VS-based gait approach, most of such studies collect gait from frontal view where sideway motion is not available. Therefore, in VS-based gait recognition, it can be useful to investigate and utilize information from sideways motion too not only from foot but perhaps from the whole body as well. It is interesting to note that from biomechanical research, Cavanagh [38] also observed that runner

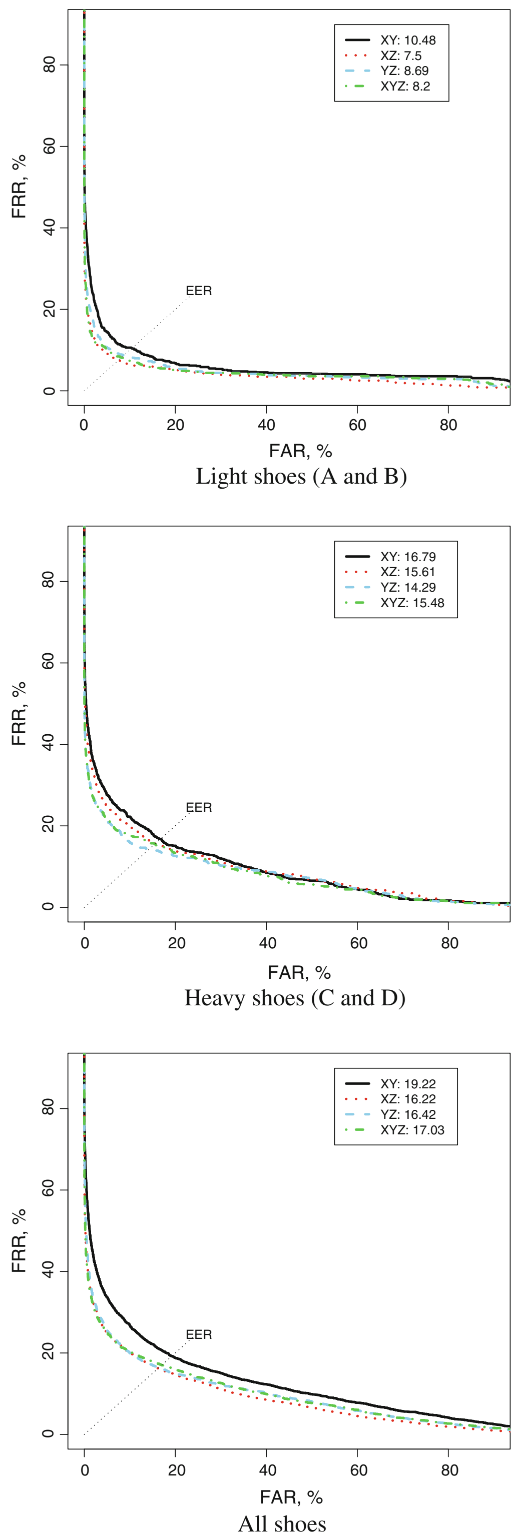

Fig. 8 Fusion performance regardless of shoe type

expresses individuality characteristics in medio-lateral (i.e., sideway) shear force. Thus, we can state following hypothesize that:

The individuality of the person's natural feet motion is most exhibited in the sideway direction of the motion compared to the up-down or forward-backward directions.

As can be expected, big and heavy footwear negatively affecting performance, especially this is noticeable in up-down and sideways directions (see Fig. 5). The reason can be attributed to the physics of the foot motion. The big and heavy footwear will require more energy and can be also uncomfortable or difficult to walk and thus individual characteristics of the natural foot motion diminish.

Although fusion appears to provide performance improvement in most cases, performance improvement in scenarios with heavy shoes or all shoes is insignificant or none (last two rows in Table 3). This suggest that the estimated weights in formula 3, which were based on data from light shoes, are not suitable for heavy shoe scenarios. Thus, in future work, it is necessary to investigate the other weighting or fusion mechanisms based not only on the directions of the motion but also on the footwear type.

It should be noted our analysis is based on data from adult men population, and one needs to take this into account when generalizing findings for other types of populations such women, children or old populations. We would also like to note that we propose foot-based authentication not as a replacement (due to error rates) but as an additional security mechanism for periodic re-verifications. Users are still required to be authenticated by means of stronger authentication mechanisms (e.g., PIN code, password, fingerprint) when first time authenticating to the system. Then, foot-based authentication can be employed as an supplementary mechanism to increase security. In order to reduce user inconvenience, one can set operating threshold such that FRR is very small or zero and FAR is medium to high. In other words, one can choose ZeroFRR[2] in the DET curve as a operating threshold, e.g., ZeroFRR with shoe type A and fusion combination *XYZ* in Fig. 7 is less than 1%.

In general, this approach would not eliminate the unauthorized access but can help to reduce it significantly. Of course, privacy aspects of such approach needs also to be understood before real applications can be developed.

6 Conclusion and future work

In this paper, we investigated a potential of 3D foot acceleration signals for user authentication purposes. In our approach, we use a wearable accelerometer sensor to collect foot motion (i.e., acceleration signals from three directions, namely up-down, forward-backward and sideways). The recognition method was based on detecting individual cycles in gait signal and then finding best matching pair between two sets of

[2] ZeroFRR is the smallest FAR where FRR is 0.

Table 3 EERs of the methods after fusion

Shoe type	Best w/fusion	XY	XZ	YZ	XYZ	Improvement (Δ_{ij})
Shoe type A	1.6	1.67	0.56	1.1	0.5	68.8
Shoe type B	2.8	1.67	1.25	1.67	1.15	58.9
Shoe type C	5	3.33	3.31	2.77	2.23	55.4
Shoe type D	3.3	1.73	3.33	1.8	1.67	49.4
Light shoes (A and B)	9.8	10.48	7.5	8.69	8.2	16.3
Heavy shoes (C and D)	16.2	16.79	15.61	14.29	15.48	4.4
All shoes	16.4	19.22	16.22	16.42	17.03	–

Numbers are given in %

gait cycles. First, we analyzed acceleration signals from three directions separately and then applied fusion techniques on several combinations of the signals with the aim of improving performance accuracy. Analyzing gait samples (sequences) from 30 subjects, we obtained EERs in the range of 0.5–19.22% depending on the direction of the motion, shoe type and fusion combination.

One of the application areas for such user authentication method can be in enhancing security by unobtrusive periodic (re-)verification of the identity. Although (relatively) small error rates of the method allow to have a practical applications in normal conditions, there are still exist challenges associated with foot-based (also gait-based in general) person recognition. Such challenging factors include surface type (e.g., stairs), walking speed (fast vs. slow) and the like. Influence of such factors into foot-based authentication methods is required to be understood for developing real-case application of the approach. In order to develop robust motion-based authentication methods, following fusion can be studied: (1) combining motion information from several body parts, e.g., foot and arm; (2) combining motion information obtained using different types of sensors, e.g., foot acceleration and foot pressure; (3) and combination of (1) and (2). It is also necessary to investigate better fusion mechanisms in case of challenging factors (e.g., when walking with heavy shoes) and evaluate approach on larger data sets.

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