Gait Authentication and Identification Using Wearable Accelerometer Sensor

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***Abstract*—This paper describes gait recognition using a body worn sensor. An accelerometer sensor (placed in the trousers pocket) is used for collecting gait features. From the acceleration signal of the person, cycles have been detected and analysed for recognition. We have applied four different methods (absolute distance, correlation, histogram, and higher order moments) to evaluate performance of the system both in authentication and identification modes. Our data set consists of 300 gait sequences collected from 50 subjects. Absolute distance metric has shown the best performance in terms of EER, which is equal to 7.3% (recognition rate is 86.3%). Furthermore, we have also analysed recognition performance when subjects were carrying a backpack.**

I. Introduction

With advances in miniaturization techniques, we are evolving toward an age where personal electronic components are gaining a processing unit and storage capacity, and those which already had them increasing in performance. Such advancement enables to broaden application usage of personal electronic devices. For example, mobile phones have grown from merely voice communication tools to devices that can also process and store private/personal data. Furthermore, they can be also used in applications such as m-banking [1] and m-government [2]. Consequently, all of these may increase the risk of being the target of an attack not only because of device's value per se but also the data stored in the device. The first important step in securing and protecting personal devices is user authentication. It is envisaged that one of the objectives of successful user authentication mechanisms in mobile devices is to provide continuous or periodic verification of a user identity, thereby ensuring identification throughout mobile device usage [3]. Another important factor that should be added to the objectives is that such mechanism should be unobtrusive and should not cause inconvenience when the device is in frequent use. In most mobile phones, password-based or PIN-based user authentication mechanisms are implemented. On the one hand, password-based authentication has some limitation from a usability perspective, e.g. managing multiple passwords, difficulties in memorizing and recalling strong long passwords, etc. On the other hand, the process of typing passwords itself requires an explicit action from the user, which might not be comfortable when mobile devices are often used. Therefore, there is still a space for improvement in mobile user authentication.

Gait (walking manner of a person) as a biometric has gained a lot of interest in recent years. From a technological point of view, biometric gait recognition can be categorized into three groups: machine vision, floor sensor and body worn sensor systems. We will refer to these 3 approaches as MV (Machine Vision), FS (Floor Sensors) and WS (Wearable Sensors), respectively. A significant amount of research on gait biometric is based on machine vision methods, where image/video processing techniques are employed to extract gait features [4], [5], [6], [7], [8]. The second category in automatic gait recognition is based on the floor sensor system [9], [10], [11]. In this approach, a set of sensors or force plates are installed on the floor, which enables to measure gait related features, like ground reaction force (GRF) [9], heel to toe ratio [10] and so on. In the third category, gait patterns are collected using a set of body worn sensors [12], [13], [14]. In this approach, people wear sensors in different places on the body, such as waist [12], hip [15], etc. User authentication based on WS gait recognition approach can meet the above mentioned requirements of a mobile authentication mechanisms. It may enable periodic verification of an identity of a mobile user in a user-friendly way. For example, whenever the validation of identity is necessary, it can be performed when a user is walking rather than requesting the user to recall and enter rarely used passwords or PIN codes.

This paper describes gait recognition using a body worn sensor. An accelerometer sensor (placed in the trousers pocket) is used for collecting gait features. From the acceleration signal of the person, cycles have been detected and analysed for recognition. We have applied four different methods (absolute distance, correlation, histogram and higher order moments) to evaluate performance of the system both in authentication and identification modes. Our data set consists of 300 gait sequences collected from 50 subjects. Absolute distance metric has shown the best performance in terms of EER, which is equal to 7.3% (recognition rate is 86.3%). Furthermore, we have also analysed recognition performance when subjects were carrying a backpack. The rest of the work is structured as follows. Section II contains a description of the experiments, section III describes applied methods, and section IV presents recognition results. Section V discusses and compares different gait recognition approaches and section VI concludes the paper.

II. Data set

For collecting acceleration data, a device called Motion Recording (MR) sensor was used [15]. It measures acceleration in three orthogonal directions (up-down, forward-backward and sideways) with a sampling frequency of about 100 observations per second. From the output of the MR sensor, we obtained resultant acceleration in units of g ($g \approx 9.8m/s^2$). Using the MR sensor we collected 300 gait sequences from 50 subjects (17 female and 33 male, in the age range 19-62). In the rest of the paper, we will refer to the gait sequence as a gait sample. For each subject 6 gait samples were collected, 4 normal walking and 2 normal walking while carrying a backpack. The weight of the backpack was about 4 kg. Each sample contained walking acceleration of the person for a distance of about 20 meters. During walking trials the MR sensor was put in the right pocket of subjects' trousers (except for one person). One subject did not have a pocket, so the MR sensor was attached to her belt. Furthermore, in each trial the sensor was taken out of the pocket and put back in to get independent measurements. After the acceleration data had been collected, it was transferred to the computer for analysis. Both normal walking, with and without the carrying backpack, were performed at the same indoor location.

III. Gait recognition methods

The time intervals between acceleration values in resultant acceleration signal are not always equal, therefore we interpolate the signal to produce equal time intervals. Then, in order to reduce the level of fluctuation in the signal, a moving average filter is applied. Each gait sample contains some standing still portion at the beginning and at the end, see Figure 1. The reason for introducing such standing still parts is that in real settings walking usually starts from standing still position. Therefore, for the authentication mechanism it is essential to be able to distinguish when person is walking naturally. Consequently, the first step consists of determining actual walking parts in the signal. Afterwards, we detect cycles and use them for recognition of the person. One cycle corresponds to two steps. Assume that $A = (a_1, a_2, ..., a_n)$ is a resultant acceleration signal after interpolation and moving averaging have been applied. Detecting walking and cycles are described below.

Detecting walking. Duration of standing stills are different for every gait sample. We experimentally found that actual walking involves acceleration around 1.3g. Therefore, we look for the first acceleration value, a_w ($1 < w < n$), which is greater than 1.3g (rectangle point in the Figure 1). Then, based on the location of a_w in the signal, cycles are searched.

Detecting cycles. We need to find a sequence $I = (a_{i_1}, a_{i_2}, ..., a_{i_m})$, which represents local minima of the acceleration signal A. Every cycle contains approximately 100 acceleration values. With the aid of this information, we search for the first minima, a_{i_1}, in the range $[a_{w-d_1}, ..., a_{w+d_2}]$ ($d_1 = 50, d_2 = 150$), i.e. $a_{i_1} = min([a_{w-d_1}, ..., a_{w+d_2}])$. This minima is considered as the start of the first cycle. The end of the first cycle is found as $a_{i_2} = min([a_{i_1+D-d}, ..., a_{i_1+D+d}])$ ($D = 100, d = 20$). The procedure is repeated until the end of the signal is reached, $a_{i_k} = min([a_{i_{k-1}+D-d}, ..., a_{i_{k-1}+D+d}])$ (circle points in Figure 1). It should be noted that the last found minima may not actually represent cycle beginning (or ending). Although they are not used in the analysis, a similar procedure from the previous stage can be applied to find when walking stops.

In the analysis, we omit the first 2 found cycles, as the first steps a person makes from the standing still position may not adequately represent his or her natural gait [16], [17]. We only use the next 6 cycles (after omitting the first 2 ones) in our analysis, see Figure 1. We have applied four methods namely, the absolute distance, correlation, histogram and higher order moments to evaluate performance of the system. For the first two methods, we calculate an average cycle. For computing the average cycle, detected cycles are normalised in time. After normalisation, each cycle contains exactly 100 acceleration values. Then, in order to reduce the effect of "unusual" steps in walking, we use median rule for computing the average cycle. Assume that $C^{(i)} = [c_1^{(i)}, c_2^{(i)}, ..., c_n^{(i)}], n = 100, i = 1, .., 6$ are the six normalised cycles of the signal. Then, the average cycle, $C = (c_1, c_2, ..., c_n)$, is calculated as follow, $c_j = median(c_j^{(1)}, c_j^{(2)}, ..., c_j^{(m)}), m = 6, j = 1, .., 100$. In other words, each acceleration value in the averaged cycle is the median (middle point) of the corresponding values in the normalised cycles. We use the average cycle of the person as a (100-components) feature vector, and compute the absolute (Manhattan) distance and correlation between feature vectors to produce a similarity score. Euclidean distance is also tested but the performance of the absolute distance was better, so we only report the results of the absolute distance. In addition, the absolute distance is computationally less expensive than the Euclidean distance, which makes the absolute distance metric more suitable in electronic devices with limited computing power. For the last two methods, we use the cycles without a prior normalisation. We calculate n-bin histogram (n=10) of the gait acceleration cycles, and use it as a feature vector. In case of higher order moments, skewness and kurtosis of the acceleration cycles are computed and used as a two components feature vector. All these methods, except the absolute distance, were applied by Mantyjarvi et al. [13], and correlation had shown the best performance on their data set.

IV. Results

To facilitate the description in this section, we introduce the following sets: S_1, S_2, S_3 and S_4 are sets of the 1st, 2nd, 3rd and 4th sample of normal walking from each subject without carrying a backpack. Cardinalities of these sets is 50, and $S_i \cap S_j = \emptyset, \forall i \neq j, i, j = 1, 2, 3, 4$. R_1 and R_2 are sets of the 1st and 2nd sample of normal walking from each subject while carrying a backpack. Cardinalities of these sets are also 50, and $R_1 \cap R_2 = \emptyset$. $S = S_1 \cup S_2 \cup S_3 \cup S_4$ and $R = R_1 \cup R_2$.

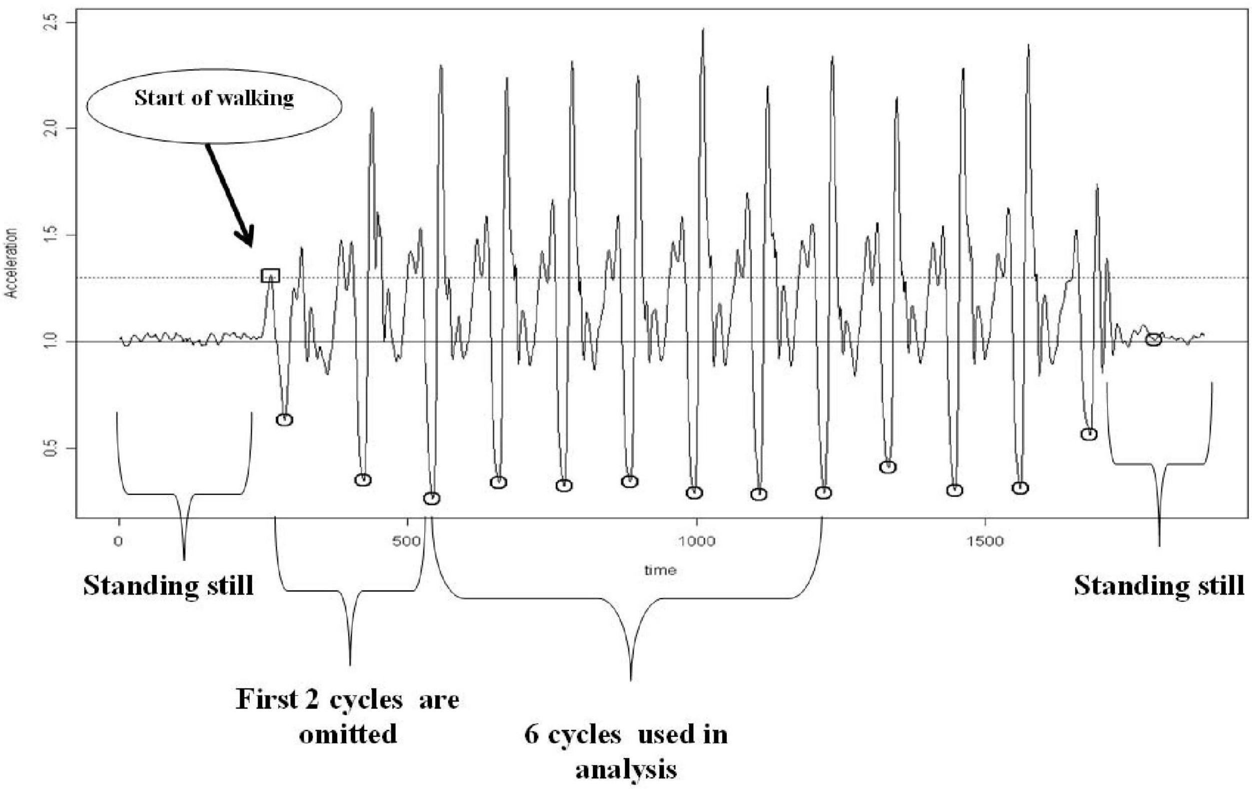

Fig. 1. An example of gait sample of the person.

A. Normal walking without carrying a backpack

In the first part of our study, we analysed normal walking samples without carrying a backpack. We hoped to produce unbiased estimates of error rates by using leave-one-out cross comparisons procedure [18]. Applying this procedure on the set S we obtained 300 unique genuine and 19600 unique impostor scores for each method. Based on these scores, FAR (False Accept Rate) and FRR (False Reject Rate) were estimated and the corresponding DET (Decision Error Trade-off) curves are shown in Figure 2. DET curve is a plot of FAR versus FRR, which shows performance of a biometric system in different operating thresholds. Usually, to express the performance of the system by a single value, an Equal Error Rate (EER) is used. The EER is the point in DET curve where FAR=FRR. The EERs of the methods are summarized in Table I (column EER). Although WS-based gait recognition approach is more suitable for authentication (verification) mode, we evaluated the performance of the system in identification mode too. For this mode, we used the Cumulative Match Characteristics (CMC) curve, which is a plot of cumulative probability versus rank [19]. First, the set S_1 was used as a gallery set (known samples), while a union of sets S_2, S_3 and S_4 was used as a probe set (unknown samples), and cumulative probabilities were estimated. Then, S_2 acted as a gallery set and the rest as a probe set. This was repeated until all sets were acted as gallery set. Finally, the cumulative probabilities at ranks were averaged for all four cases. The corresponding CMC curves are shown in Figure 3. Identification probabilities at ranks 1, 2 and 3 are given in Table I (columns P_1, P_2 and P_3, respectively). Identification probability at rank 1 corresponds to the recognition rate.

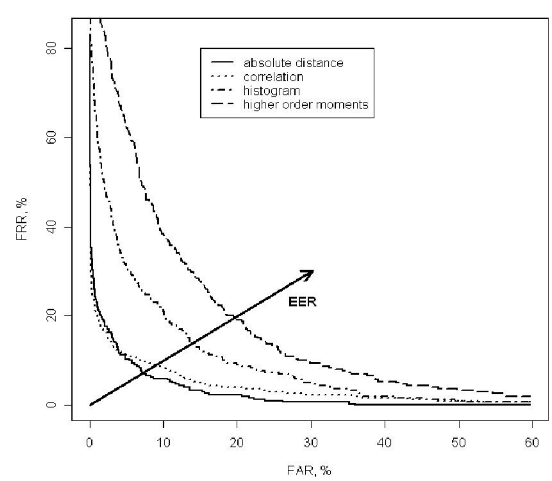

Fig. 2. Decision error trade-off (DET) curves.

In both authentication (in terms of EER) and identification

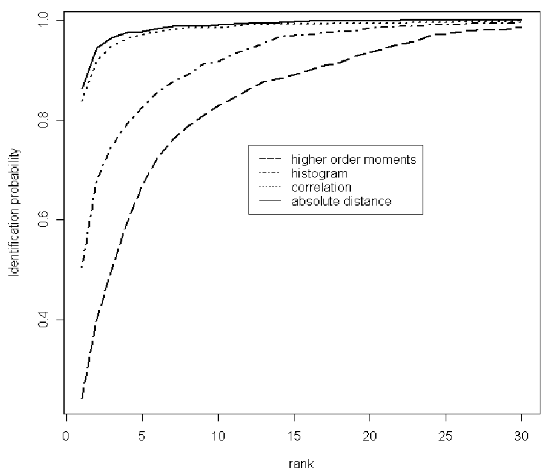

Fig. 3. Cumulative Match Characteristics (CMC) curves.

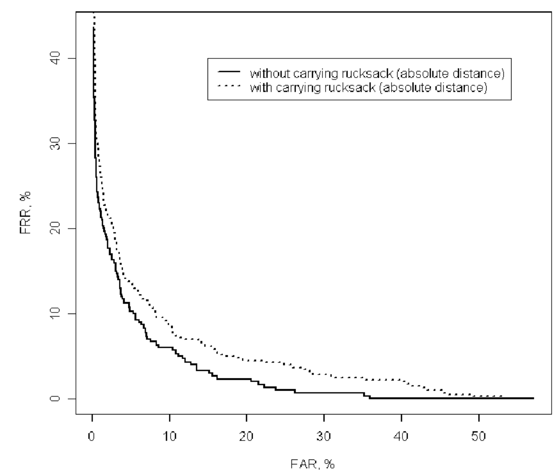

Fig. 4. DET curves with and without carrying a backpack.

TABLE I
NUMERICAL SUMMARY OF THE METHODS. ALL NUMBERS ARE IN %.

Method	EER	P_1	P_2	P_3
Absolute distance	7.3	86.3	94.5	96.5
Correlation	9.2	83.8	91.8	94.8
Histogram	14	50.5	68	74.8
Higher order moments	20	24.2	40.2	50
Carrying backpack (Ab. dis.)	9.3	86.2	92.5	93.8

modes, although the absolute distance metric showed the best performance, the correlation method's performance was not significantly different from it. In identification mode, recognition rates (at rank 1) of histogram and higher order moments were very low, although significantly higher than pure chance (2%).

B. Normal walking with carrying a backpack

In the second part of our analysis, we checked the influence of carrying a backpack on the recognition performance. We only report results using the absolute distance metric, since the difference between absolute distance and correlation methods is not very significant. We performed comparisons between samples in the set of normal walking without carrying a backpack and samples in the set of normal walking while carrying a backpack. In other words, every sample from the set S was compared to each sample in the set R, thereby generating sets of genuine and impostor containing 400 genuine and 19600 impostor scores, respectively. FAR and FRR were estimated based on these sets of genuine and impostor scores. The resulting DET curve is shown in Figure 4. In terms of EER, performance deteriorated from about 7.3% to about 9.3%. For the identification case, each set $S_i, i = 1, 2, 3, 4$ acted as a gallery set while the set R was used as a probe gallery. Then, identification probabilities were averaged over all 4 cases. The CMC curve is shown in Figure 5. Identification probabilities at ranks 1, 2 and 3 are shown in Table I (last row). Recognition rate (identification probability at rank 1) dropped slightly from 86.3% to 86.2%.

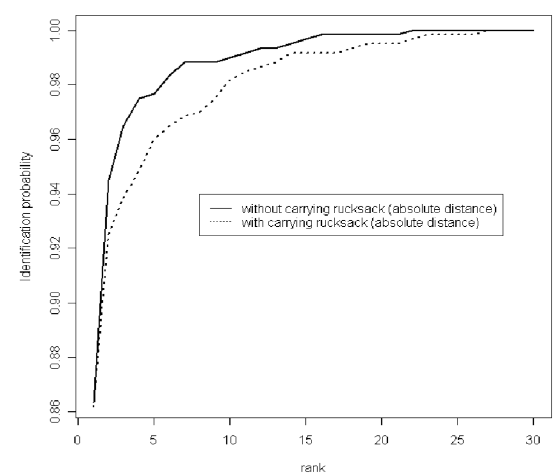

Fig. 5. CMC curves with and without carrying a backpack.

V. DISCUSSION AND COMPARISON

A summary of several gait recognition approaches is presented in Table II. In the table, columns "**S#.**", "**Perf. %**" and "**Catg.**" represent the number of subjects used in experiments, performance of the system in terms of EER (studies [4], [5], [12], [13], [14], [15]) and recognition rate (studies [6], [9], [11], [10]), and gait recognition category to which the study belongs, respectively. This table by no means implies a direct comparison of the performances, mainly due to the differences between data sets. Nevertheless, it gives a general overview of some approaches in gait recognition.

All three MV, FS and WS gait recognition approaches share common challenges that can alter walking of the person

TABLE II
A SHORT SUMMARY OF SEVERAL GAIT RECOGNITION APPROACHES.

Study	**S#**	**Perf. %**	**Catg.**
BenAbdelkader et al. [4]	17	11	MV
Wang et al. [5]	20	8, 12, 14	MV
Wagg and Nixon [6]	115	64, 84	MV
Orr and Abowd [9]	15	93	FS
Suutala and Roning [11]	11	65.8-70.2	FS
Middleton et al. [10]	15	80	FS
Ailisto et al. [12]	36	6.4	WS
Mäntyjärvi et al. [13]	36	7, 10, 18, 19	WS
Gafurov et al. [14]	21	5, 9	WS
Gafurov et al. [15]	22	16	WS
This paper	50	7.3, 9.2, 14, 20	WS

like lower limb injury, drunkenness, aging, etc. However, FS and WS approaches lack difficulties of MV gait systems such as noisy background subtraction, lighting conditions, viewing angle and so on. Apart from technological difference among MV, FS and WS, another significant difference between these gait recognition approaches is in their application area. Usually, MV gait systems are employed in surveillance and forensics applications [20]. FS gait recognition can be installed in the entrances of the buildings for access control. In addition to providing identity information, FS system can also give location and direction of the user within area of installation [9]. Applications of WS gait recognition approach can be in the area of authentication and protection of mobile and portable electronic devices, when sensors are integrated into the hardware of the devices.

Previously, WS gait based analysis had been successfully applied in the area of clinical and medical studies to monitor patients with locomotion disorders [17], [21]. In clinical settings, such approach is considered as simple, cheap and portable, compared to vision based motion captured system [16]. Person recognition using WS gait approach was reported by Ailisto et al. [12] and Mäntyjärvi et al. [13]. For recognition, they used acceleration from the waist of the person, and sampling frequency of their accelerometer sensor was 256 Hz [12], [13]. In addition, they detected individual steps and did not consider sideway acceleration. In our previous works we utilized acceleration of ankle and hip for authentication [14], [15], see Figure 6. In the case of the ankle based recognition, a sensor with sampling frequency of 16 Hz was used [14], while in the case of the hip based recognition a sensor with 100 Hz sampling rate was used [15]. All these [12], [13], [14], [15] mentioned works reported performance of gait recognition in authentication mode, while in this paper we evaluated performance both in authentication and identification modes. Moreover, in these studies [12], [13], [14], [15] the accelerometer sensor was fixed at a specific body part, while in our work it was not fixed but merely put in the pocket of the subjects. From an application perspective, this may imply that a WS gait recognition mechanism can also be used in personal gadgets which are not fixed and could be carried in the pocket. Another important distinguishing factor in our work is a size of the data set. The number of people participating in our experiment is larger than in other WS gait recognition approaches from Table II (to our knowledge, it is the largest in WS gait recognition area so far).

Fig. 6. Accelerometer sensor on the ankle and hip in [14] and [15], respectively.

One of the factors that may affect natural walking of a person is carrying a load. Actually, there are two tasks (not necessarily unrelated) when load carriage is involved: (1) verifying whether a person is carrying an object/load and (2) finding out how carrying an object/load influences recognition performance. BenAbdelkader and Davis [22] studied the possibility of detecting whether or not a person carrying an object by exploiting shape and periodicity cues of the human silhouette shape. A correct detection rate of 85% and a false alarm rate of 12% were obtained using 41 sequences of people walking and carrying an object [22]. In our work, we also studied the effect of carrying a backpack on recognition performance. The influence of carrying a load (e.g. briefcase) on gait recognition was previously studied in vision-based approaches [8]. In a study by Sarkar et al. [8], carrying a briefcase of about 6 kg negatively influenced performance, for example the recognition rate dropped to 61% when the difference between the template and the test gait samples was only in a briefcase (experiment H), and when the difference was in the briefcase and the shoe type it decreased to 57% (experiment I). In our case, the performance of the recognition system also deteriorated when people were carrying a backpack. However, the decrease in performance is not very significant (at least in terms of identification probability at rank 1). Such insignificance can be partly attributed to the lighter weight of the backpack and the fact it being carried on the trunk. Besides, carrying a load may have a different impact on MV and WS gait recognition approaches. For instance, in MV gait recognition carrying an object can influence not only dynamics of the gait but may also create a challenge for the silhouette extraction or the background subtraction processes.

There is also a limitation in our approach. For example, the cycle detection procedure may not adequately work when subjects walk very fast or very slow, as the procedure is velocity dependent. For coping with such types of signals, more advanced cycle and walking detection procedures might be necessary. It should also be noted that we do not claim that user authentication using wearable sensors should be considered as a sole authentication mechanism, mainly because of higher error rates compared to the other types of biometric modality (e.g. fingerprints). However, it can be used as an additional mechanism for improving security and enhancing usability of the system. It has been shown that performance of the recognition system can be increased when gait biometric is integrated with other types of biometric modalities, e.g. voice [23].

Below we summarize the main differences between this paper and works in [12], [13], [14], [15]:

- evaluating the performance of the WS-based gait recognition both in authentication and identification scenarios;
- evaluating the performance of the WS-based gait recognition when carrying a backpack;
- location of the accelerometer sensor;
- sampling frequency of the accelerometer sensor (except in [15]);
- larger sample size.

VI. Conclusion

In this paper we presented a gait recognition system using wearable accelerometer sensor. Performance on a moderate data set (300 gait sequences from 50 subjects) is promising. The main technological differences between our approach and most of the other related WS gait recognition works are in a sampling frequency of accelerometer sensor, its positioning and larger sample size. In addition, we also tested recognition performance when subjects were carrying a backpack weighting about 4 kg. Our findings indicate that although there is a decrease in performance, it is not very significant. As a part of our future work, we will expand our gait data set to include more samples from a larger number of subjects, and at the same time to include other challenging factors that may influence gait of a person (e.g. carrying bag in the hand). It is also interesting to apply WS-based gait analysis in applications such as, differentiating between men and women, or youngsters and elderly.

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