

Gait Identification Using Accelerometer on Mobile Phone

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Abstract— In this paper, we present two approaches for identification based on biometric gait using acceleration sensor - called accelerometer. In contrast to preceding works, acceleration data are acquired from built-in sensor in mobile phone placed at the trouser pocket position. Data are then analyzed in both time domain and frequency domain. In time domain, gait templates are extracted and Dynamic Time Warping (DTW) is used to evaluate the similarity score. On the other hand, extracted features in frequency domain are classified using Support Vector Machine (SVM). With the participation of total 11 volunteers over 24 years old in our experiment, we achieved the accuracy of both methods respectively 79.1% and 92.7%.

Keywords—behavioral biometric; accelerometer; pattern recognition; gait identification

I. INTRODUCTION

The explosion of mobility nowadays is setting a new standard for information technology industry. Mobile devices such as smart-phones and tablets more and more become popular, and hence, making people increasingly depend on them for their superior functionality. Such devices are commonly used for storage and retrieval of information like e-commerce and m-banking [1]. However, they can be easily lost, stolen, or illegally accessed [2]. That means sensitive or/and important information of users could be retrieved unexpectedly.

Consequently, identification has evolved to become a more priority issue for developers. Currently, the most common methods are PIN and passwords which are not always effective considering security aspects [2, 3]. These limitations can be solved using approaches based on biometric such as face recognition [4], fingerprint [5], etc. However, as these methods require explicit action from the users, they are obtrusive and inconvenient in frequent use. Thus, a more friendly mechanism of identification is desired to be developed and aim to set a new standard in mobile security.

Human gait has been introduced as a particular style and manner of moving human feet [6]. In a more detail level view, the mechanism of human gait involves synchronization between the skeletal, neurological and muscular system of human body [6]. Therefore, gait characteristics will vary from people to people. Gait

recognition has been studied as a behavioral biometric for decades. Its techniques could be typically divided into 3 categories: Machine Vision Technology (WVT) [7, 8], Floor Sensor Technology (FST) [9], and Wearable Sensor Technology (WST) [10]. WST is recognized as the most approachable and newest of all. Sensors in WST are attached to human body in various positions, such as pockets, waist or shoes to record physical motions. WST takes advantage of mobile devices' sensing capabilities including GPS, accelerometer, and gyroscope sensor, etc. Thus, it will provide developers an edge over improving various techniques in identification.

In this paper, we propose identification method based on WST using an integrated accelerometer on mobile phone. Moreover, because segmentation of gait cycles is the most important process in any gait analysis, we also provide a novel algorithm to partition gait cycles when the device is placed at trouser pocket. The rest of this paper is organized into 4 sections. Section 2 presents the related work. Section 3 presents proposed methods for identification. Section 4 summaries result from experiment. Finally, conclusion and further work will be presented in Section 5.

II. RELATED WORKS

In 2005, H. Ailisto et al. were the first to propose the gait authentication based on wearable accelerometer. In their paper, acceleration data was analyzed to find individual steps, normalize, and align them with the template. This data would be then analyzed through cross-correlation, which was used as a measure of similarity. The EER of this method was 6.4% [11].

On the other hand, S. Terada et al. positioned accelerometer on ankle to collect and analyze data [12]. From observation, they were able to draw a conclusion: The swing phase in gait cycle varies from people to people. Evaluation measurement and threshold value together yielded the judgment of gait identity. The EER was 20% at the threshold value of 1700.

Differently, A. Annadhorai et al. designed a system consisting of two wireless sensor nodes: one is a base station, and the other is a custom-designed sensor board. The board is designed with a tri-axial accelerometer and a bi-axial gyroscope. It was placed at the leg to record motions.

Features, which were extracted from time domain for each sensor stream such as mean, median, standard deviation, RMS value, and amplitude, were used for classification and recognition. The accuracy is approximately 100% due to the fact that they experimented on a small dataset [10].

While most of these systems based on standalone accelerometer (SA) have been implemented with a variety of success rate, they still have some limitations. For example, SA is relatively expensive, and the interface of some special sensors needs to be developed separately. Thus, there is an increasing need to develop an easy-to-operate gait monitoring system within pervasive environment. The recent development of mobile technology places a significant advantage in this endeavor.

Gait identification has been initially experimented on mobile phone during recent years. In 2009, S. Sprager et al. used built-in accelerometer in Nokia cellphone positioned at the hip to collect and analyze gait signal [13]. Feature vectors for classification were built based on collected data using dimension reduction on cumulants by Principal Component Analysis (PCA). The classification in this module was accomplished by Support Vector Machines (SVM). They achieved about 90.3% accuracy. In comparison to SA, built-in accelerometer in mobile phone has a lower sampling rate that may influence the accuracy of the system. Derawi et al. [14] applied Holien's work [15] using accelerometer in mobile phone instead of standalone sensor and achieved EER of 20.1% compared to 12.9%. The sampling rate of Derawi's device is around 40 – 50Hz, whereas the high quality dedicated accelerometer used in Holien's work has approximately 100Hz.

III. PROPOSED METHODS

We paid particular attention to the position of accelerometer. The mobile phone was vertically fixed at the pocket location as shown in figure 1. This position turned out to be the most appropriate for the mobile phone bearer [2]. A detailed description of milestones in gait identification will be explained in the following



Fig. 1. 3-D coordinate of accelerometer and phone attached to the trouser pocket position

A. Data acquisition

Acceleration data were acquired when user walked naturally as shown in figure 2. We performed our studies on Google Android HTC Nexus One phone. This phone has the built-in Bosch Sensortec's 3-axis BMA 150 accelerometer which measures acceleration forces up to $\pm 2g$. The sampling rate is approximately 27 Hz by setting to SENSOR_DELAY_FASTEST mode on Android SDK. Based on the relationships between gravity, acceleration and

motion, we present the output of accelerometer as 3-component vectors

$$A = [A_x, A_y, A_z]$$

where A_x, A_y, A_z represent the magnitude of the forces acting on three directions respectively.

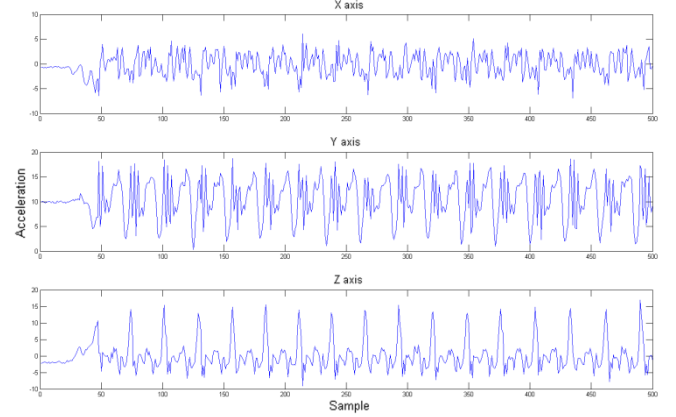


Fig. 2. Acquired 3-D acceleration signal when walking

B. Time Interpolation

Due to power saving function and the built-in accelerometers in mobile phone are simpler than standalone sensors, the sampling rate is rather low. Time intervals between two consecutive acceleration values are also not equal. Sensor only outputs value when the forces acting on each dimension have a significant change. Therefore, we interpolated the acquired signal to 32 Hz using linear interpolation to ensure that the time interval between two sample-points will be fixed.

C. Noise elimination

When accelerometer samples movement data by user walking, some noises will inevitably be collected. These additional noises could have come from various sources (e.g., idle orientation shifts, screen taps, bumps on the road while walking). A digital filter needs to be designed to eliminate noises. Multi-level wavelet decomposition and reconstruction method were adopted to filter the signal.

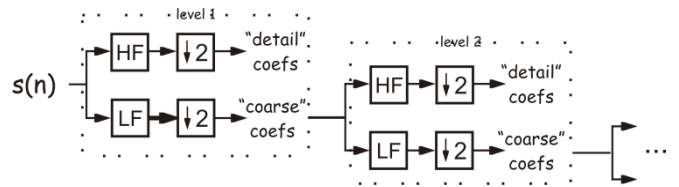


Fig. 3. Multi-level wavelet decomposition

According to figure 3, original signal is denoted by $S(n)$. High-pass filter and low-pass filter are denoted by HF and LF. Within each level, the outputs from high-pass filter are known as detail coefficients. On the other hand, low-pass filter outputs contain most of the information of the input signal. They are known as coarse coefficients. The signal is down-sampled by 2 at each level. Coefficients obtained from the low-pass filter are used as the original signal for the next

level, and continues until the desired level is achieved.

In contrast, reconstruction is the reverse of decomposition process. To eliminate noises, we assign the detail coefficients to 0. The reconstruction of the signal is computed by concatenating the coefficients of high-frequency with low-frequency. During experiment, the Daubechies orthogonal wavelet (Db6) was adopted for signal decomposition and noise reduction. Figure 4 shows the signal after noise reduction using Db6 at level 2.

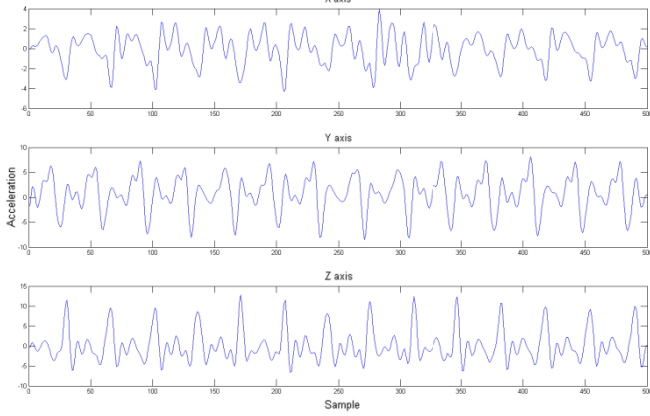


Fig. 4. 3-D acceleration after noise reduction

D. Gait cycle partition

Gait cycle is defined as the time interval between two successive occurrences of one of the repetitive events when walking [16]. In other words, two consecutive steps form a gait cycle. As shown in figure 5, the cycle starts with initial contact of the right sole, and then it will continue until the right sole contacts the ground again. The left goes through exactly the same series of events as the right, but displaced in time by half a cycle.

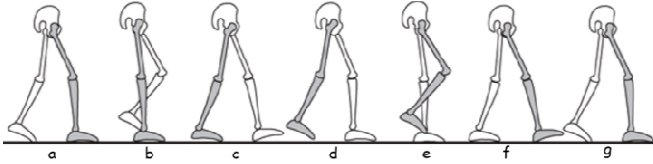


Fig. 5. Illustration of a gait cycle

When mobile phone is fixed at trouser pocket position, gait characteristics and footsteps are displayed clearly on the Z-axis of accelerometer. Instead of using all 3-dimension signals, we only used Z-dimension for gait cycle partition and feature extraction. When the sole touches the ground in phase “a” or phase “g” as in figure 5, the association between ground reaction force and inertial force together make the z-axis signal strongly changes and form peaks with the high magnitude. These peaks are called true peaks (TPs) as shown in figure 6. We designed an algorithm to detect these TPs as follows:

The original signal is denoted as $S(n)$. First, we extract a set of peaks P from $S(n)$. A data point is called peak if its value is greater than its previous and next one.

Let

$$P = \{d_i \mid d_i > d_{i+1} \wedge d_i > d_{i-1}\} \text{ with } i \in [1 \dots n] \quad (1)$$

where d_i is the i^{th} value in $S(n)$. Threshold T is estimated to filter TPs using equation (2). The peaks which have magnitudes greater than T are identified as set of TPs R :

$$T = \mu + k\sigma \quad (2)$$

$$R = \{d_i \in P \mid d_i \geq T\} \quad (3)$$

where μ, σ are mean and standard deviation of all peaks in P respectively and k is the user-defined constant. Figure 6 shows the threshold T with different k values. In our experiment, choosing $k = \frac{1}{3}$ gave the best partition rate.

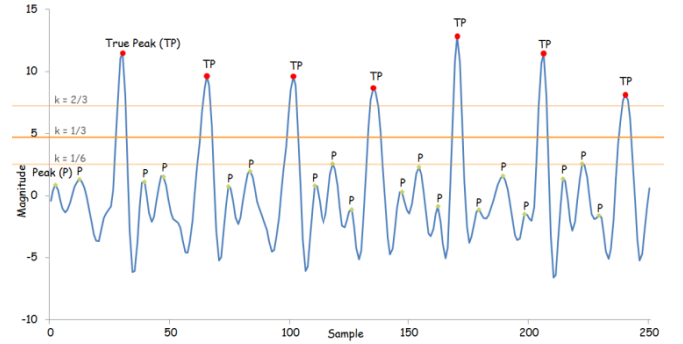


Fig. 6. Illustration of true peaks R and the thresholds T with various k values

E. Feature Extraction

1) Time domain features.

In this approach, we extract average gait cycles (AGCs) based on partitioned gait cycles [14]. A cycle is called “average cycle” if it is the most similar to the other cycles (figure 7). The AGCs will be considered as the gait templates.

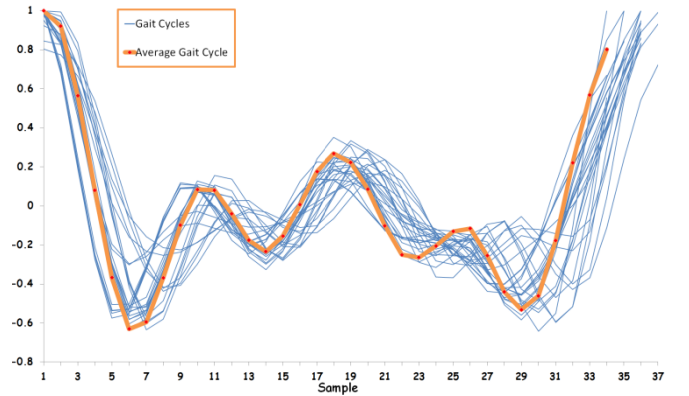


Fig. 7. Gait cycles and average gait cycle

Ideally, user should walk with a constant speed and a walking pattern. This would lead to fix the gait cycle length. In fact, the walking speed of users could not be constant. Walking speed varies from step to step. Hence, the number of data points in every gait cycle is not identical. Therefore, similarity measures based on direct template matching such as Euclidean distance, Manhattan distance are not suitable because they require the same number of data points. By

using Dynamic Time Warping (DTW), we could avoid normalizing the length of gait cycles.

To extract AGCs, the magnitude samples of each gait cycle are normalized to value between -1 and +1, and then its distance to every other are calculated using DTW

$$dtw_{i,j} = dtw(gaitcycle_i, gaitcycle_j) \quad (4)$$

where $i = 1, 2 \dots N-1, N$; $j = 1, 2 \dots N$ and N is the total number of extracted gait cycles. We obtain a $N \times N$ symmetric distance matrix. After that, we calculate the average distance d_i of one specific cycle to all others. The AGC which has the lowest d_i will be considered as a feature template

$$AGCs = \{gaitcycle_i \mid d_i = \text{agrmin}(\frac{1}{N-1} \sum_{j \neq i}^N dtw_{i,j})\} \quad (5)$$

In training phase, AGCs are extracted to be considered as gait templates. Later, these templates are labeled with a corresponding person. Given an unlabeled gait cycle in testing phase, the similarity score between the input and each template is evaluated using DTW. The label is determined to the most similar template.

2) Frequency domain features.

Fast Fourier Transform is calculated on Z-dimension acceleration signal. Theoretically, the size of window frames should be invariant with 50% overlapping from previous one. As mentioned above, the length in each gait cycle is not constant. Ordinarily, each step which is executed by normal subjects of 18-49 ages, takes an average of 0.87- 1.32 seconds in free-speed walking [16]. The sampling rate of our device after interpolation is 32Hz. That means each gait cycle contains from 28 to 42 data points. As a result, the length of every gait cycle needs to be normalized so that the combination of consecutive gait cycles will be fixed into a window frame.

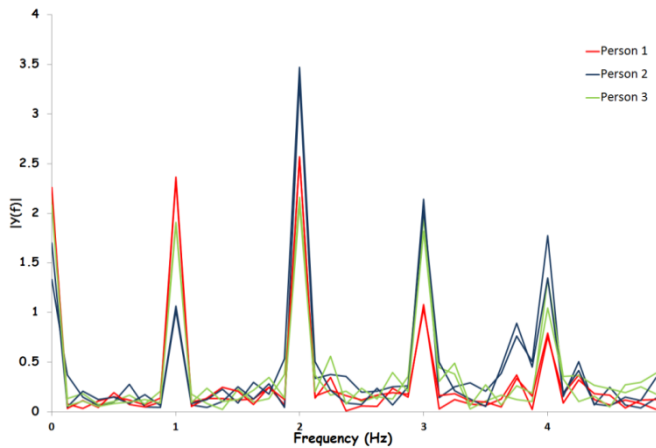


Fig. 8. The first 40 FFT coefficients

Assume the i^{th} gait cycle can be expressed as $GC^i = \{S_k \mid k \in [1 \dots K]\}$, where S_k is the value of k^{th} data point and K is the length of this cycle. T is the expected length to be normalized. Firstly, we calculate the absolute distance D between two consecutive data point S_j and S_{j+1} . Secondly,

we find the position p that has the minimum distance D_{min} .

$$D_j = |S_j - S_{j+1}| \quad \forall j \in [1 \dots N-1] \quad (6)$$

$$p = (t \in [1 \dots N-1] \mid \forall j \in [1 \dots N-1]. D_t < D_j \wedge t \neq j) \quad (7)$$

After that, the new data point is generated by calculating the mean value between the two data point at position p and its next one

$$S_{new} = \frac{S_p + S_{p+1}}{2} \quad (8)$$

We have two situations:

- If $K < T$, S_{new} is added to the position between S_p and S_{p+1} .
- Otherwise if $K > T$, S_p is replaced by S_{new} , and remove S_{p+1} .

This process repeats until $T = K$.

In our method, the number of data point in each gait cycle was normalized to 32. Fast Fourier Transform (FFT) was calculated using a 256-sample window frame. We split data into windows of eight consecutive gait cycles. Each window would overlap the previous one by 50% (4 gait cycles). The first 40 FFT coefficients as shown in figure 8 formed a feature vector. Support Vector Machines (SVM) was applied on feature vectors for classification in training phase, and prediction in testing phase.

IV. RESULT

We experimented on data collected from accelerometer in Google Nexus One phone. The phone position was fixed at the pocket location (figure 1). A total of 11 volunteers from over 24 year-old participated in data collection. Each volunteer was asked to walk as naturally as possible on the ground floor. They walked for an overall of 12 laps with 36 seconds on each lap. 5 of 12 lap data were picked randomly for training phase and the other 7 lap data were used to predict.

TABLE I. CONFUSION MATRIX OF THE RECOGNITION IN TIME DOMAIN

	A	B	C	D	E	F	G	H	I	J	K	Acc.
A	34	0	2	0	0	1	0	0	0	5	0	81.0
B	0	31	0	3	0	1	0	0	0	1	0	86.1
C	0	1	34	1	0	0	0	0	0	0	0	94.4
D	0	0	5	25	0	0	0	0	0	0	0	83.3
E	1	0	0	1	22	0	0	0	0	6	0	73.3
F	0	4	2	1	2	27	0	0	0	0	0	75.0
G	0	0	0	0	2	0	21	7	0	3	3	58.3
H	0	0	0	0	0	1	6	27	0	2	0	75.0
I	0	0	0	0	0	0	0	0	21	3	0	87.5
J	1	0	0	0	1	0	2	0	0	32	0	88.9
K	2	1	2	0	1	0	3	0	0	1	20	66.7
Overall Avg.												79.1

All of our experiment methods were developed on Java and Android SDK. They could be deployed and run directly on mobile phone. We also used libsvm [18] for SVM classification. The obtained result is illustrated as the confusion matrix in table 1 and table 2 for both methods. Each letter (A-K) represents a label of each volunteer. The

recognized classes are ordered in vertical direction while the reference classes are in the horizontal direction. By applying two different methods in time domain and frequency domain, the overall accuracy of 79.1% and 92.7% were achieved respectively.

TABLE II. CONFUSION MATRIX OF THE CLASSIFICATION IN FREQUENCY DOMAIN

	A	B	C	D	E	F	G	H	I	J	K	Acc.
A	30	0	0	5	0	0	0	0	0	0	0	85.7
B	0	30	0	0	0	0	0	0	0	0	0	100.0
C	0	0	25	0	0	0	0	0	0	0	5	83.3
D	0	0	0	25	0	0	0	0	0	0	0	100.0
E	0	0	0	0	30	0	0	0	0	0	0	100.0
F	0	0	0	0	0	36	0	0	0	0	0	100.0
G	0	0	5	0	0	0	30	0	0	0	0	85.7
H	0	0	0	0	0	0	6	27	0	0	0	81.8
I	0	0	0	0	0	0	0	0	25	0	0	100.0
J	0	0	0	0	0	0	6	0	0	30	0	83.3
K	0	0	0	0	0	0	0	0	0	0	20	100.0
Overall Avg.												92.7

V. CONCLUSION AND FUTURE WORK

In this paper, we analyzed acceleration signal for user identification based on biometric gait. Template matching (in time domain) and machine learning (in frequency domain) are the two main approaches in this experiment. As stated, the advantage of identification based on biometric gait lays on the implicit operation, which achieved more friendliness from users. The result indicates the fact that it is possible to implement biometric systems on mobile phone in practice. With similar templates extracted in time domain as Derawi's work [14], we also achieved the equivalent result when testing on our dataset. However, the accuracy can be improved significantly by an approach using machine learning in frequency domain. The obtained rate of 92.7% using FFT and SVM is high, but needs additional validation on a larger dataset. Meanwhile, the information retrieved has not been specified in this method. Furthermore, we would like to take a deep look into characteristic of each gait to retrieve information specifically. As stated, we also provided a novel algorithm to segment gait cycles when mobile phone is positioned at the trouser pocket. Since this is the important step in gait analysis, refining the effectiveness of this process is our objective to achieve the higher result.

In our experiment, data were collected from volunteers in the same day. Unfortunately, the biometric gait of each individual is different day by day [17]. Nonetheless, gait identification needs to be applied in any circumstance. Mobile phone position is not also meant to be static. These will become our challenge for further analysis. From the best of our knowledge, since no public dataset has been published within this research field, it makes the comparison among research works more difficult to appraise. Hence, constructing a public dataset with participation of students in campus is also our ambition.

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