Chinese Journal of Electronics
Vol.20, No.3, July 2011

Gait Authentication Based on Acceleration Signals of Ankle*

LI Yuexiang[1], WANG Xiaobo[1] and QIAO Feng[2]

(1.*School of Computer and Information Technology, Shanxi University, Taiyuan 030006, China*)

(2.*Faculty of Information and Control Engineering, Shenyang Jianzhu University, Shenyang 110168, China*)

Abstract — A novel feature points based gait authentication method is introduced in this paper, which uses the acceleration signals acquired from an ankle-mounted 3-axis accelerometer. Feature points are extracted from original gait samples. A dynamic time wrapping algorithm is employed to match the feature points of different samples and calculate the distortions. Based on these distortions, a multi-criterion model is designed for authentication. The experimental result shows that the extracted feature points can represent the original signals good enough in authenticating with one accelerometer, and the equal error rate of this method is only 3.27%, better than that of the previous literatures reported.

Key words — Gait authentication, MEMS accelerometer, Feature points, Dynamic time warping, Multi-criterion model.

I. Introduction

Biometric systems, such as fingerprint, face, and voice recognition systems, are becoming increasingly important as they can offer more reliable and efficient ways of authentication than traditional methods, like using PIN code. As a newly developed biometric recognition technology, gait authentication has gained a lot of interest in recent years. From technological point, gait recognition systems can be categorized into three classes: machine vision based (MV-based)[1], Floor sensor based (FS-based)[2] and Wearable sensor based (WS-based).

Gait signals of MV-based system can be captured by video cameras from a distance, and then video/image processing techniques are used to extract gait features for identity recognition. Most of the current gait recognition methods belong to this category. There are already some open gait video databases, *e.g.* the CMU Motion of Body (MoBo) database developed by Carnegie Mellon University, and the CASIA Gait Database provided by the Institute of Automation, Chinese Academy of Sciences.

In FS-based system, gait data are collected by a set of sensors installed on the floor. When a person walks on them, the sensors can measure the data such as ground reaction force and heel-to-toe ratio.

WS-based gait recognition technology is relatively new, especially with the development of MEMS technology; sensors are increasingly miniaturized and integrated, and have been widely used in gesture recognition[3], kinematics analysis[4] *etc.* In this method, gait signals are recorded by wearable sensors and then utilized for individual identification.

Ailisto *et al.* first proposed the gait authentication method based on acceleration signals[5]. They used a waist-mounted accelerometer to collect gait data. Their method is firstly finding individual steps, normalizing and averaging them. Then the each step is aligned with the template and cross-correlation is calculated, which is used as a measurement of similarity. An Equal error rate (EER) of 6.4% is achieved in tentative experiments of 36 test subjects finally. Besides, there are many studies based on several other methods, such as frequency domain analyze, distribution statistics and K-nearest neighbor[6−8], and the results (measured in EER) are between 5.6% and 19%.

Huang *et al.* built a pair of intelligent shoes for gait identification[9]. Gait data was collected from 6 sensors (force sensor, bend sensor, switch sensor, accelerometer, gyroscope and ultrasonic sensor) installed in each shoe. Utilizing these gait parameters, they applied Cascade neural networks with Node-decoupled extended Kalman filtering (CNN-NDEKF) for modeling and classifier generating. The EER of this method is 3.07%.

Gafurov *et al.* conducted a study of gait authentication using the acceleration signals acquired from participants' right ankle[10]. The cycle length comparison and the histogram similarity were used, and the EER of 5% and 9% were achieved respectively. In their work, accelerations from three axes are combined. Since the lateral signal is relatively less stable and distinctive, the combination of the three axes may lead to a poorer recognition capability. Moreover, in the cycle length method, only the first 16 observation points are used to make comparison. It will lower the accuracy when walking speed changes.

A novel Feature point method (FPM) for gait authentication is developed in this paper. Feature points are extracted from the original acceleration signals in two directions: Backward-forward (BF) and vertical. The Dynamic

*Manuscript Received Oct. 2010; Accepted Mar. 2011.

time warping (DTW) algorithm is employed to match the feature points and calculate the distortions of two gait samples from different directions. Based on these distortions, a multi-criterion model is designed to identify individuals. The experimental result shows that the extracted feature points can represent the original signals good enough for authenticating only with one accelerometer, and the performance of this method is better than that of previous literatures.

II. Data Acquisition and Dataset

1. Acceleration acquiring device

In order to acquire gait signals, we design an acceleration acquiring device which consists of one μPD78F0485 microcontroller from Renesas Electronics, and one 3-axis digital accelerometer with three axes pointing to BF, vertical and lateral directions, respectively. The device is also equipped with a 1GB Flash memory for acceleration data storage, and a USB interface module for data transmission. This device is 85mm long, 55mm wide, 25mm height, weighs 46g and is powered by a Li-battery. It can be easily mounted on user's ankle. The acceleration acquiring device and the attachment of the device are shown in Fig.1.

2. Data acquisition

The participants include 22 healthy persons (16 male and 6 female; aged 23 to 52; height from 1.62 to 1.83 meters; weight from 42 to 71kg), walked in normal speed for about 20 meters. Each participant repeated 4 times, from which obtained 4 specimens per person. One of the examples of acceleration signals in vertical, BF and lateral directions is shown in Fig.2. The X axis are observation point number, the Y axis are magnitude of accelerations in vertical, BF and lateral directions respectively. By analyzing the acceleration signals, it is found that the BF and vertical signals are more stable and distinctive than the lateral signals. Therefore, the accelerations in these two directions are chosen as the investigated subjects in this paper.

3. Cycle partition

Gait acceleration signals generated from user's walking are cyclical. In normal, each cycle is about 0.8s $\sim$1.2s, in which there are about 40 data points at 40Hz sampling rate. Acceleration signal is divided into cycles by searching the local maxima of the BF accelerations. For each specimen, the maximum among the first 40 data is regard as the first division, and the index of this maximum is denoted by m. Then we find the maximum of the next 40 data beginning with $m+20$, and it is chosen as the second division. The above steps are repeated until the last data. Fig.3 shows cycle partitions of an acceleration signal with 300 sample points, the gait cycles of T1$\sim$T6 are marked with circles.

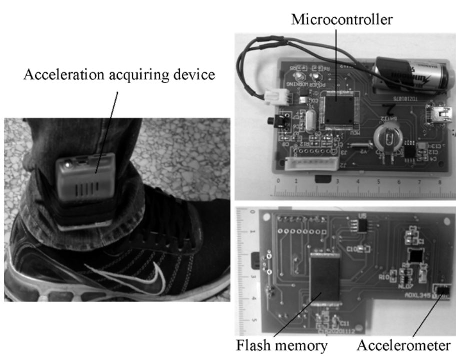

Fig. 1. Acceleration acquiring device and attachment

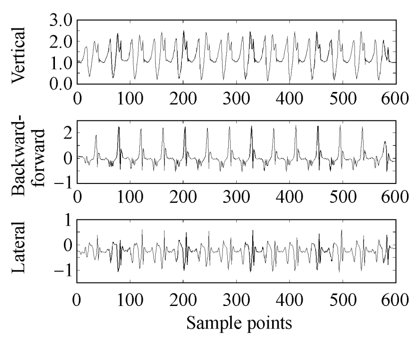

Fig. 2. Fragments of Gait acceleration signals in three directions

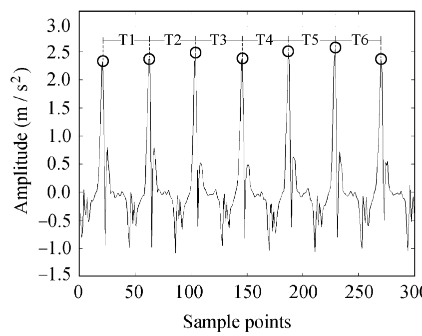

Fig. 3. Cycle partition

4. Dataset component

Our dataset contains 22 persons' gait signals in BF and vertical directions, and each person has 4 specimens. As the first several steps and the final steps may not adequately represent a person's natural gait, we choose 4 continuous cycles in the middle of a specimen as a sample. Therefore, there are 4 samples for each person and 88 samples in total. Each sample consists of 4 cycles in BF direction and 4 cycles in vertical direction.

III. Feature Point Method

The idea of Feature point method (FPM) is to extract feature points from acceleration signals. Verification is recognized by comparing the similarities between different samples according to the extracted feature points.

1. Feature point extraction

The feature points are extreme points of acceleration signals. In this paper, we use the zero-crossings of Wavelet transform (WT) approach to extract feature points from each cycle. The WT of a signal $f(x)$ is given by the convolution product as follows.

$$W, f(x) = (f * \psi_s)(x) = \int_{-\infty}^{+\infty} f(y)\psi_s(x-y)dy,$$

where $\psi_s(x)$ is the dilation of $\psi(x)$:

$$\psi_s(x) = \frac{1}{s}\psi\left(\frac{x}{s}\right)$$

Let $\theta(x)$ be a smoothing function, and

$$\psi(x) = \frac{d\theta(x)}{dx}.$$

We denote $\theta_s(x) = (1/s)\theta(x/s)$, the dilation of $\theta(x)$ by a factor of s, which satisfies

$$\int_{-\infty}^{+\infty} \theta(x)dx = 1, \qquad \lim_{|x|\to\infty} \theta(x) = 0.$$

So, $\psi_s(x)$ can be a mother wavelet function, and we can derive that:

$$W_s f(x) = f * \left(s\frac{d\theta_s}{dx}\right)(x) = s\frac{d}{dx}(f * \theta_s)(x)$$

Hence, $W_s f(x)$ is proportional to the first derivation of $f(x)$ smoothed by $\theta_s(x)$, and the zero-crossings of $W_s f(x)$ correspond to the extreme points of the smoothed signal. It is observed experimentally that the extreme points can be extracted accurately when Gaussian function is used as a smoothing function, and Gaussian wavelet, which is the first derivation of the Gaussian function, works as the mother wavelet.

We divide the feature points into crest and trough groups according to the wavelet coefficient. For each feature point, we use 2 parameters to describe it: amplitude (magnitude of a feature point) and time (the position of a feature point in a cycle). As a result, each gait cycle can be described by 8 parameters, which are time and amplitude sequences of crests in BF direction, time and amplitude sequences of troughs in BF direction, time and amplitude sequences of crests in vertical direction, time and amplitude sequences of troughs in vertical direction.

During a natural walking, it is hard to move at a constant speed. The cycle length and the position of feature points may differ consequently. To overcome the difficulty, we use a normalized time sequence $T_N = \{T_1, T_2, \cdots, T_i, \cdots, T_n\}$ to substitute for the original time sequence $T = \{t_1, t_2, \cdots, t_i, \cdots, t_n\}$ $(1 \le i \le n)$, where n is number of feature points.

$$T_i = \frac{t_i - t_1}{t_n - t_1}, \qquad i \in [1, n].$$

After normalization, the length of all gait cycles is equal to 1.

2. Distortion calculating with DTW

Generally, the walking speeds are different individually. One also cannot maintain his/her walking speed all the time. It means that the number of feature points may differ in different cycles and they are not homogeneous distribution in each cycle. The distortion with previous situation can be calculated by DTW algorithm, which can obtain the minimal warping path during the derivation. Points on warping path illustrate the optimal corresponding relations between tow feature point sequences.

Take two samples E and V in BF direction as an example to obtain the distortion using DTW algorithm. Suppose $T_E\{t_{e1}, t_{e2}, \cdots, t_{em}\}$, $A_E\{a_{e1}, a_{e2}, \cdots, a_{em}\}$ are the crests in a cycle of E, and $T_V\{t_{v1}, t_{v2}, \cdots, t_{vn}\}$, $A_V\{a_{v1}, a_{v2}, \cdots, a_{vn}\}$ are that of V, where T_E and T_V are time sequences, A_E and A_V are amplitude sequences, m and n are the lengths of sequences. After matching with time sequences, we can obtain the accumulated distance $\gamma(m, n)$ of point (m, n) using the DTW equation as follow, which is the crest time distortion between T_E and T_V, written in D_{CT}.

$$\gamma(i,j) = \delta(i,j) + \min[\gamma(i-1,j), \gamma(i-1,j-1), \gamma(i,j-1)] \quad (1)$$

where the distance function δ can be determined by the following formula.

$$\delta(m,n) = |t_{em} - t_{vn}|$$

The minimal warping path P can be determined during the calculation of γ shown in Fig.4. In Fig.4, T_E is in horizontal and T_V is in vertical coordinates. Each crossing point (i, j) $(1 \le i \le m, 1 \le j \le n)$ is correspond to the difference between te_i and tv_j. The crest amplitude distortion in BF direction of sample E and V can be calculated based on the corresponding relations illustrated in P represented by D_{CA}.

In a similar way, we can determine the trough time distortion D_{TT} and trough amplitude distortion D_{TA}. So we can calculate for 4 distortions in one direction within one cycle.

Because there are 4 gait cycles in each sample, we can obtain 4 groups for total 16 distortions in BF direction. Each group contains 4 distortion variables, time distortion of crest D_{CT}, amplitude distortion of crest D_{CA}, time distortion of trough D_{TT} and amplitude distortion of trough D_{TA}. Let the average of all crest and trough time distortions be the overall time distortion, represented by D_{BF-T} as follows.

$$D_{BF-T} = \frac{1}{16}\sum D_{CT} + \frac{1}{16}\sum D_{TT}$$

In the same way, the overall amplitude distortion can be obtained as follow.

$$D_{BF-A} = \frac{1}{16}\sum D_{CA} + \frac{1}{16}\sum D_{TA}$$

In the similar way, the overall distortions in vertical direction, D_{V-T} and D_{V-A}, also can be easily achieved. These distortions are used to illustrate the similarities between two samples and are regarded as criteria of gait authentication.

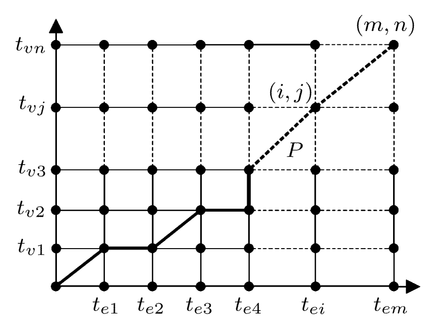

Fig. 4. DTW warping path

3. Multi-criterion model

In order to improve the recognition accuracy, a multi-layer model is designed as in Fig.5, including 4 levels based on D_{BF-T}, D_{V-T}, D_{BF-A} and D_{V-A}.

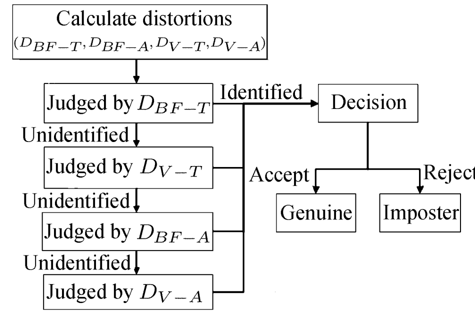

Fig. 5. Multi-criterion model

D_{BF-T} is used in the first level of this model. If D_{BF-T} is smaller than a lower-threshold, the verification is accepted, if it is larger than an upper-threshold, then verification is rejected, otherwise it is regarded as the unidentified sample and moves to the next level D_{V-T}. The judgment strategy used in D_{V-T} and D_{BF-M} level follows the same rules as D_{BF-T}. As the final criterion, , we set a single threshold for the level of D_{V-A}. If D_{V-A} is smaller than this threshold, verification is accepted; otherwise it is rejected. The thresholds of all criteria are determined by experiments.

IV. Experiments and Analysis

To evaluate the performance of FPM, we randomly select 15 persons' samples as the training dataset, and the rest 7 persons' samples are used to test. The thresholds of all criteria are determined by conducting experiments on training dataset. This paper is based on the judgment criteria of False acceptance ratio (FAR), False rejection ratio (FRR) and Equal error rate (EER), which are commonly used in biometric identification systems, using the test dataset to compare the results of FPM with correlation method.

Let the comparison between the different samples of one person be the genuine trial, and the comparison between different people be the imposter trial. Then, FAR is the ratio of misjudgments in genuine trial, FRR is the ratio of misjudgments in imposter trial, and EER is the larger one between FRR and FAR when FRR equals to FAR or the distance between them is the smallest. EER illustrates the characteristic of this system. The higher EER is, the worse this recognition system performed.

1. Thresholds of multi-criterion model

Samples from the training dataset are used to determine the thresholds. The lower-threshold of the first level criterion can be determined by finding the maximal D_{BF-T} when FRR=0, and the upper-threshold is the minimal D_{BF-T} when FAR=0. Similarly, the thresholds of the second and the third level criterion D_{V-T} and D_{BF-A} can be determined. The threshold of the bottom level D_{V-A} is the value when FAR equals to FRR or the distance between them is the smallest.

Using the training dataset, we generate $15 \times C_4^2 = 90$ genuine trials and $C_{15}^2 \times C_4^1 \times C_4^1 = 1680$ imposter trials as the samples of the model. Based on the preset threshold and judged by D_{BF-T}, the 16 genuine trials and 613 imposter trials are identified correctly, and the rest unidentified 74 genuine trials and 1067 imposter trials are regarded as the input samples of next level criterion of D_{V-T}. In the same way, there are 60 genuine trials and 886 imposter trials need to be verified in the third level criterion of D_{BF-A}, and finally 57 genuine trials and 47 imposter trials enter the last level of D_{V-A}. The corresponding relation of different range of D_{V-A}, FRR and FAR is shown in Table 1.

It is seen that the different between $FRR = 3.3\%$ and $FAR = 2.6\%$ are the smallest. So we choose the average value of corresponding D_{V-A} (5461∼5509) as the threshold of D_{V-A}, which equals to 5492. In this case, the false acceptance number is 43 and the false rejection number is 3, and $FAR = 2.6\%$ and $FRR = 3.3\%$ illustrates $ERR = 3.3\%$, which reaches our expectation. The thresholds of the multi-criterion model are shown in Table 2.

Table 1. D_{V-A} Thresholds with FRR and FAR

Threshold	FAR	FRR	$\lvert FAR - FRR \rvert$
5367 ∼ 5415	4.8%	2.7%	2.1%
5416 ∼ 5444	4.8%	3.0%	1.8%
5445 ∼ 5460	4.8%	3.3%	1.5%
5461 ∼ 5509	2.6%	3.3%	0.7%
5510 ∼ 5522	2.4%	3.6%	1.2%
5523 ∼ 5539	2.4%	3.9%	1.5%
5540 ∼ 5553	0	3.9%	3.9%

Table 2. Thresholds of the multi-criterion model

Dis	GTS	ITS	FRs	FAs	Thresholds	
					L-Th	U-Th
D_{BF-T}	90	1680	0	0	0.24	0.56
D_{V-T}	74	1067	0	0	0.36	0.73
D_{BF-A}	60	886	0	0	1000	4440
D_{V-A}	57	47	3	43	5492	

Notes:
Dis Distortion, L-Th: Lower-threshold,
U-Th: Upper-threshold, GTS: Genuine trial samples,
ITS: Imposter trial samples, FAs: False acceptances,
FRs: False rejections.

2. Performance of FPM

Based on the thresholds determined by the multi-criterion model, the performance of FPM is evaluated on the testing dataset. We use $7 \times C_4^2 = 42$ genuine trials and $C_7^2 \times C_4^1 \times C_4^1 = 336$ imposter trials as the judgment object and the result is shown in Table 3. The false acceptance number is 11 and the false rejection number is 1, which lead to the results of $FAR = 11/336 = 3.27\%$ and $FRR = 1/42 = 2.38\%$, so ERR equals to 3.27%. The result illustrates FPM is effective.

Table 3. Results of the multi-criterion model

Dis	Thresholds		GTS	ITS	Results	
	L-Th	U-Th			FRs	FAs
D_{BF-T}	0.24	0.56	42	336	0	0
D_{V-T}	0.36	0.73	39	173	0	0
D_{BF-A}	1000	4440	24	73	0	0
D_{V-A}	5492		20	69	1	11

Notes:
Dis Distortion, L-Th: Lower-threshold,
U-Th: Upper-threshold, GTS: Genuine trial samples,
ITS: Imposter trial samples, FAs: False acceptances;
FRs: False rejections.

3. Comparision with the correlation method

Correlation method is a statistical technique illustrating whether and how strongly pairs of variables are related. Ailisto *et al.* use this method in their gait authentication research[5]. We compare the effectiveness of FPM given in this paper with correlation method. Coefficients of the BF and the vertical signals are calculated respectively with any two different samples, determined by their average value. We choose the larger one as the correlation value of these two samples as represented by Ailisto *et al.*[5]. If the correlation value is larger than the pre-set threshold, then verification will be accepted, otherwise it will be rejected.

Table 4 lists some of thresholds and the corresponding of FAR and FRR. Clearly, $EER = 4.8\%$ is achieved when the coefficient threshold is 0.947 ∼ 0.949, where $FAR = FRR =$

4.8%, which is 1.5% higher than FPM's. This result shows FPM achieves better performance than correlation method.

Table 4. Coefficient thresholds with FRR and FAR

Threshold	FAR	FRR	$\|FAR-FRR\|$
0.940	6.5%	2.4%	4.1%
0.941 ∼ 0.942	6.3%	2.4%	3.9%
0.943 ∼ 0.946	6.0%	4.8%	1.2%
0.947 ∼ 0.949	4.8%	4.8%	0%
0.95	3.9%	4.8%	0.9%
0.951	3.6%	4.8%	1.2%
0.952	3.0%	4.8%	1.8%

4. Results and analysis

Based on the previous results, the FPM reaches higher accuracy in identification than correlation method. The Detection error tradeoff (DET) curves with these tow methods are shown in Fig.6, we can see that FRR corresponding to the FPM is smaller than that of the correlation method when FAR of the two curves are equal. Similarly, when FRR of the two curves are equal, FAR of FPM is also smaller than that of the correlation method. Especially when the values of FRR and FAR are close, this tow parameters of FPM are all smaller than correlation method. So, the conclusion is drawn that the overall performance of FPM is superior to that of the correlation method. And the EER of FPM with only one accelerometer also achieve the same performance with the method represented by Huang *et al.*[9], in which they used 6 sensors to identify.

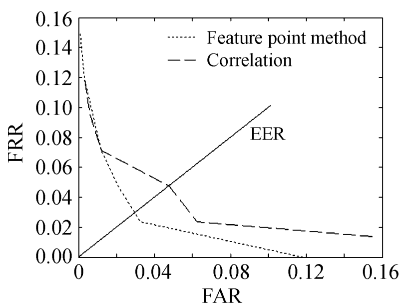

Fig. 6. DET curves

V. Conclusions and Future Work

In this paper we have presented a novel FPM on gait authentication. The BF and vertical acceleration signals are selected and represented by a serial of feature points extracted by zero-crossings of WT. The DTW algorithm is used to calculate the distortions between two samples and a multi-criterion model is designed for authentication based on time and amplitude distortions. The experimental results show that FPM achieves better performance than that of previous methods.

But as a behavioral biometrics, gait characteristics can be affected because of injuries, carrying of a heavy load or tiredness. Further studies are required on how to reduce the effectiveness caused by these factors in gait authentication method, which would improve the practicability and expand the usage range of the gait authentication.

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LI Yuexiang was born in 1958. She is an associate professor of the School of Computer and Information Technology, Shanxi University. Her main research interests include low power consumption system, embedded system and their applications. (Email: lyx_1958@yahoo.com.cn)

WANG Xiaobo was born in 1985. He is currently a M.S. candidate in the School of Computer and Information Technology, Shanxi University. His current research interests are micro inertia measurement system and its application.

QIAO Feng is a professor of the Faculty of Information and Control Engineering, Shenyang Jianzhu University. His main research interests include intelligent systems and control.