33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

The PLR-DTW Method for ECG Based Biometric Identification

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***Abstract*—There has been a surge of research on electrocardiogram (ECG) signal based biometric for person identification. Though most of the existing studies claimed that ECG signal is unique to an individual and can be a viable biometric, one of the main difficulties for real-world applications of ECG biometric is the accuracy performance. To address this problem, this study proposes a PLR-DTW method for ECG biometric, where the Piecewise Linear Representation (PLR) is used to keep important information of an ECG signal segment while reduce the data dimension at the same time if necessary, and the Dynamic Time Warping (DTW) is used for similarity measures between two signal segments. The performance evaluation was carried out on three ECG databases, and the existing method using wavelet coefficients, which was proved to have good accuracy performance, was selected for comparison. The analysis results show that the PLR-DTW method achieves an accuracy rate of 100% for identification, while the one using wavelet coefficients achieved only around 93%.**

I. Introduction

PERSONAL identification is very important in modern society and has been extensively used in many fields. Biometric authentication provides airtight security by identifying an individual based on the physiological and/or behavioral characteristics [1]. Each individual has unique biometric characteristics, which include physiological traits such as face, fingerprint, palm, iris, vein and behavioral characteristics like gait and keystroke.

Recently, the unique property of electrocardiogram (ECG) has been used as a biometric for human identification. The validity of using ECG for biometric identification is supported by the fact that the geometrical differences of the heart in different individuals display certain uniqueness in their ECG signals [2]. The ECG signal varies from person to person due to the differences in position, geometry, size, physiological feature of the heart, structures of thoracic cavity, age, weight, sex, body type and many other factors. A typical ECG wave of a normal heartbeat consists of a P wave, a QRS complex and a T wave, as shown in Fig. 1.

The ECG biometric does provide a simple alternative methodology, which may be appropriate in certain applications, e.g., patient identification in medical data monitoring, physical access control and medical records management. For example, the ECG based biometric identification will enable family members to easily share a remote health monitoring device without the need to input user names and/or passwords. It can also be used together with other biometric measures, as a complementary feature, for fusion in a multimodal system to improve the identification performance.

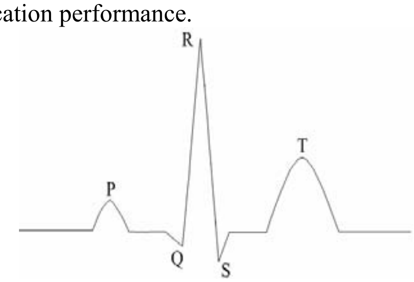

Fig. 1. Basic shape of an ECG signal segment

There exist a variety of methods to utilize ECG signals as a biometric source, however the accuracy performance remains a problem for them to be actually applied. This study proposes a new method, named as PLR-DTW method, where the Piecewise Linear Representation (PLR) is used to keep important information of ECG signal segments while reduce the data dimension if necessary, and the Dynamic Time Warping (DTW) is used for similarity measures between signal segments. The analysis results based on several ECG databases indicate that the proposed method is able to obtain an improved accuracy performance compared to existing methods.

II. Existing Work

Shen *et al*. [3] proposed to exact several temporal and amplitude features from the QRST wave of one-lead ECG, combine a template matching method and a decision-based neural network to implement the identity verification system. Their experimental results of 20 participants achieved 100% accuracy rate.

By combining analytic and appearance based features, Wang *et al*. [4] achieved high recognition accuracy rate. Principal component analysis (PCA) and linear discriminate analysis (LDA) are used for data reduction and feature extraction. A method for feature extraction without fiducial detection based on a combination of

This work was supported in part by National Basic Research Program 973 (No. 2010CB732606), Key Basic Research Program of Shenzhen China (No. JC201005270257A), and Guangdong Innovation Research Team Fund for Low-cost Healthcare Technologies.

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autocorrelation and discrete cosine transform (AC/DCT) is proposed to completely relax fiducial detection. Israel *et al.* [5] extracted 15 features, which are time duration between detected fiducial points and reduced to 12 during the feature selection process. This system was tested on a database of 29 subjects and reached a 100% human identification rate and a heartbeat recognition rate of 81%.

By using a distance measure based on wavelet transform, Chan *et al*. [6] presented an evaluation of the biometric based on electrocardiogram (ECG) waveforms. The one-lead ECG signals were collected from 50 subjects, and the wavelet distance measure has a classification accuracy of 89%, which is more efficient than the two other measures mentioned in their study. In another study [7], the discrete wavelet transform is also applied for the ECG biometric, and the verification rate reached 100% for 35 normal subjects and 10 arrhythmia patients. We can see from the results that the discrete wavelet coefficients method is efficient for databases with more subjects, and thus is used for performance comparison in this study, where the ECG templates will be decomposed with level-6 decomposition by the Daubechies scalar wavelet, i.e. Db3.

III. Method

A. Preprocessing

For each of the ECG record, a segment of 20-second data sequence is kept for the experiment analysis. We use a Butterworth bandpass filter of which the cutoff frequency is 0.5 Hz - 40 Hz to denoise the ECG data, for example, removing the power-line interferences. Then, the R-peaks are detected by using mathematical morphology method. The heartbeats of each sequence are truncated by a window of 0.8 second entered at R-peak. The first and last heartbeats are eliminated to get full heartbeat signals. Any heartbeat, with a correlation coefficient below one standard deviation of the mean correlation coefficient, was discarded; this was done to avoid the inclusion of PQRST complexes that had been corrupted by large intermittent noise. The remaining heartbeats were used to compute an amplitude normalized single-averaged heartbeat.

B. Feature extraction

To extract the effective features of time series, compress data and improve the efficiency of algorithms, several time series model representations have been proposed for dimension reduction. The common model representations of time series include frequency domain representation, e.g. the discrete Fourier transform (DFT) and the discrete wavelet transform (DWT), piecewise linear representation (PLR) [8], and *etc*. The DFT and DWT method are based on the distance between points, so they can not depict the important features of time sequences, i.e. the dynamic properties, while the PLR method can extract the main features of time series and reduce the data dimension effectively.

The key idea of PLR is to discard minor fluctuations and keep major minima and maxima. The parameter Z is used to control the compression rate. An increase of Z leads to a selection of fewer points, and vice versa. By connecting the important points with line segments, we can get piecewise linear representation of time series.

Fig. 2 gives an example of the PLR of an ECG template. It can be denoted as a two-dimensional array. The second dimension which represents the amplitude of the left points for similarity comparison as the Comparison Vector (CV) is kept. The PLR process is not necessary if the original sampling points of ECG template are few enough.

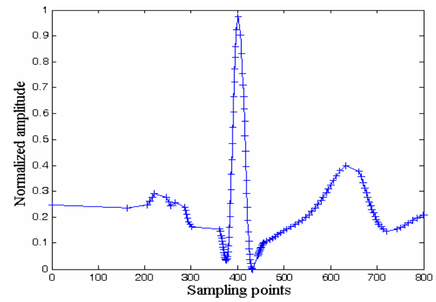

Fig. 2. The PLR of the original signal

C. Classification

Dynamic Time Warping (DTW) [9] method is used to measure the similarity between the CVs. Compared with the Euclidean distance measure, the DTW method is much more robust, allowing similar shapes to match even if time series are out of phase in the time axis.

Suppose we have two time series, S and T, of length m and n, respectively, where

$$S = s_1, s_2, ..., s_i, ..., s_m \tag{1}$$

$$T = t_1, t_2, ..., t_j, ..., t_n \tag{2}$$

We construct an m-by-n matrix $A_{m\times n}$ according to the sort of their time positions. Each matrix element $a_{ij} = d(s_i, t_j) = \sqrt{(s_i - t_j)^2}$ corresponds to the alignment between the points s_i and t_j. A warping path W is a contiguous set of matrix elements that defines a mapping between S and T, and the k^{th} element of W is defined as $w_k = (a_{ij})_k$. The warping path is typically subject to several constraints:

(1) $\max\{m,n\} < K < m+n-1$;

(2) $w_1 = a_{11}, w_k = a_{mn}$;

(3) Given $w_k = a_{ij}$, $w_{k-1} = a_{i'j'}$, where $0 \le i - i' \le 1$, $0 \le j - j' \le 1$

Then, we can get the path that minimizes the warping cost:

$$DTW(S,T) = \min(\sum_{i=1}^{K} w_i) \tag{3}$$

The DTW method can be summarized as: finding the cumulative distances of the minimum cost of bending by using the dynamic time warping. $D(m,n)$ is the minimum cumulative distance of the curved path, i.e.

$$\begin{cases} D(1,1) = a_{11}, \\ D(i,j) = a_{ij} + \min\{D(i-1,j-1), D(i,j-1), D(i-1)\} \end{cases} \tag{4}$$

which is used to find the dynamic time warping path. An example of the DTW path is illustrated in Fig. 3.

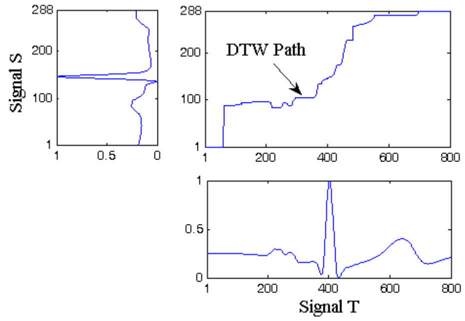

Fig. 3. Dynamic time warping path

Consider the situation that some of the piecewise linear representation of the ECG templates have different lengths while the DTW can combine time planning with distance measure, we chose it to measure the distance between CVs.

D. Decision-Making

In a biometric identification, the test feature vector is compared to many or all biometric templates stored in the system, while in a biometric verification, the feature vector is only compared to the claimed biometric template in the system.

In our identification process, the test signal was compared to all the enrolled templates. A threshold, denoted as δ, was set to distinguish whether the subject belongs to the database. The DTW distances between the test signal and all enrolled templates shall be calculated. If the lowest DTW distance is higher than the threshold δ, then the tester is rejected; otherwise, the tester associated with the enrolled template with the lowest DTW distance is selected as a match.

IV. PERFORMANCE ANALYSIS

For the performance study, we used ECG data from three databases: the public database PTB [10] and MIT-BIH Normal Sinus Rhythm database [11], and the one collected under the lab environment.

The false acceptance rate (FAR), false rejection rate (FRR) and half total error rate (HTER) were calculated to evaluate the performance of the PLR-DTW method. The DTW distance is used as the measure in the decision-making process. Given a system threshold β, false acceptance happens when the DTW distance between an enrolled template and a test signal from different subjects is smaller than β, while false rejection happens when the DTW distance between an enrolled template and a test signal from the same subject is larger than β.

Though FAR/FRR is an important indicator to evaluate the performance of any biometric systems, an accuracy rate calculated according to the decision-making process described in Section III.C is actually used to evaluate this ECG-based identification process. The threshold δ for distinguishing whether the subject belongs to the database shall be selected based on the FAR/FRR performance analysis. To minimize the error of false rejection, it is suggested to set δ as

$$\delta \geq \min(\beta|_{FRR=0}) \tag{5}$$

Then, the accuracy rate of the proposed identification system is calculated as the total number of testing samples divided by the total number of correctly verified samples.

A. Results from the MIT-BIH Database

For the MIT-BIH Normal Sinus Rhythm database, subjects were found to have no significant arrhythmias, and the database was sampled at 128 Hz. We chose 14 subjects to analyze the proposed method according to the length of the records. Since each of the subjects has only one record, we use the first 20 seconds of the record to get the enrollment template and keep the last 20 seconds for testing. Since the sampling rate is only 128 Hz, there is no need to use the PLR method for dimension reduction. The accuracy rate of the DTW method is 100% while the result of the wavelet coefficients method is 92.9%. The minimum of the HTER is 0.002 and the curves of FAR and FRR of the DTW method are shown in Fig. 4.

B. Results from Self-Collected Database

For the self-collected database, one-lead ECG signals sampled at 500 Hz were captured from 15 participants. The enrollment templates and testing data were obtained in a similar way to the MIT-BIH database. The accuracy rate of the DTW method is 100% while the result of the wavelet coefficients method is 93.33%. The minimum of the HTER is 0.057 and the curves of FAR and FRR are shown in Fig. 5.

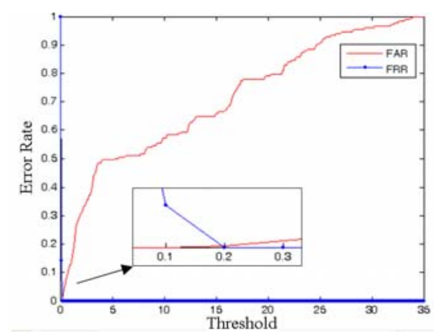

Fig. 4. Curves of FAR and FRR with MIT-BIH database

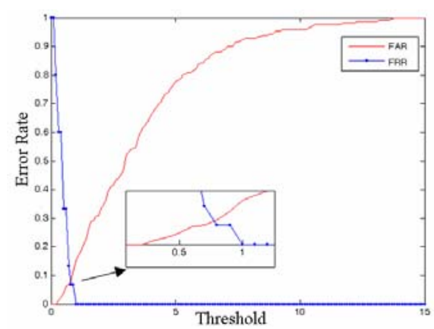

Fig. 5. Curves of FAR and FRR with self-collected database

C. Results from the PTB Database

We selected 13 healthy subjects of different age and sex in the PTB database. The signals were sampled at 1000 Hz with a resolution of 0.5 μV. Each of the 13 subjects has at least two recordings. The two records are collected a few days even a few years apart. We use one record from each subject for the enrollment, and another for testing.

According to results from the MIT-BIH Database and self-collected database, we set the threshold $\delta = 1$. We first use PLR to reduce the dimension of the templates. With the increase of parameter Z, fewer points left, and the accuracy rate changes. Fig. 6 depicts the accuracy rate with different values of Z from 0.01 to 0.25, and the step is set to be 0.005. The fitting error between the compressed data by PLR and the original data is also shown in Fig. 6.

It can be seen that with the increase of Z, fitting error has a trend of ascent while the accuracy rate fluctuates. The accuracy rate increases with the increase of Z until $Z = 0.05$, then the accuracy rate decrease, and the top value is 100%. Therefore, Z was set to be 0.05 in the following analysis. Then we calculate FAR/FRR to evaluate the performance of the PLR-DTW method when Z = 0.05, and the curves of FAR and FRR are shown in Fig. 7 while the minimum of the HTER is 0.121.

For comparison, the performance of wavelet coefficients method was also evaluated with the same database. The accuracy rate is 92.3%.

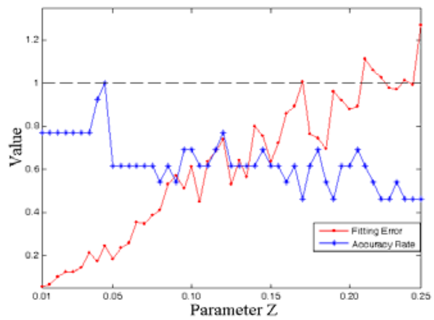

Fig. 6. Effects of the PLR parameter Z (including accuracy rate and fitting error)

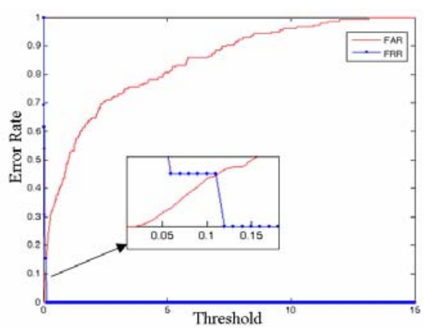

Fig. 7. Curves of FAR and FRR with PTB database

It can be seen from the results that the PLR-DTW method obtained higher accuracy rate than the wavelet coefficients method, and it is also suitable for one-lead ECG signals. On the other hand, because this method does not rely on the fiducial of different parts of the heartbeat waveform, it has much lower computational complexity.

V. Conclusion

In this study, a new method, called PLR-DTW method, was proposed for ECG biometrics, where the piecewise linear representation is deployed to decrease the template dimension if necessary, and the Dynamic Time Warping method is used for similarity measure between two signals. The analysis results of accuracy rate and FRR/FAR with three ECG databases indicates that the PLR-DTW method has better performance than many existing methods, while with lower computational complexity. This method is suitable for one-lead ECG signal as well. Nevertheless, the number of subjects for performance analysis is still limited, and more extensive experiments shall be carried out in the near future. We also consider combining different ECG identification methods for improved system reliability.

Acknowledgment

This work thanks for the experimental data provided by Joint Research Center for Biomedical Engineering, The Chinese University of Hong Kong.

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