ECG IDENTIFICATION SYSTEM USING NEURAL NETWORK WITH GLOBAL AND LOCAL FEATURES

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ABSTRACT

This paper proposes a human identification system via extracted electrocardiogram (ECG) signals. Two hierarchical classification structures based on global shape feature and local statistical feature is used to extract ECG signals. Global shape feature represents the outline information of ECG signals and local statistical feature extracts the information between signals in time domain. Genetic algorithm based back propagation neural network is used as the specific classifier. Experiment results show that our identification system can achieves an average 97.6% accuracy on a 38 subjects of PTB public ECG database and an average 100% accuracy on an 18 subjects of MIT-BIH public ECG database, which demonstrates the proposed system can reach satisfactory effects.

KEYWORDS

ECG, Global shape feature, Local statistical feature, two hierarchical classification structures

1. INTRODUCTION

Automatic human identification using physiological modality has been widely researched as its significance in many security areas. A lot of works have been studied on human identification such as facial features (Samaria and Harter, 1994; Nagamine *et al*, 1992), gait (Kale *et al*, 2003), fingerprint (Hodges and Pollack, 2007), and iris (Zhu *et al*, 2000) etc. However, these biometrics modalities either can not provide reliable performance in terms of identification accuracy or are not robust enough against falsification. Electrocardiogram (ECG) is a method to measure and record different electrical potentials of the heart, which is considered to be a unique system of each person. The main reason to use ECG signals to identify individuals is due to its physiological and geometrical differences (Hoekema *et al*, 2001).

Recently, ECG signals for human identification have been widely studied. To build an efficient ECG human identification system, the very important element is the distinctive features extracted from ECG signals. Some methods are proposed for ECG feature extraction. Kyoso and Uchiyama (2001) present a system which identifies subjects based on a comparison of a person's ECG with previously registered ECG feature parameters. These feature parameters are sampled from the intervals and durations of the electrocardiographic wave extracted using characteristic points appearing on the waveform of the second order derivative and are identified using discriminate analysis. Wang *et al.* (2013) proposed ECG signals for human identification based on sparse representation of local segments, which is extracted from an ECG signal and projected to a small number of basic elements in a dictionary. Biel *et al.* (2001) extracted attributes that are temporal and amplitude distances between detected fiducial points. They proposed two extraction methods called analytic-based method and appearance-based method.

In this paper, two different features of ECG signal have been extracted as global shape feature and local statistical feature. Due to the different representation information of those two kind features, a two hierarchical classification structure has been designed mainly spired by the idea of changing large class number problem to small class number problem. In the comparison phase, genetic algorithm based back propagation neural network (GA-BPNN) combined classifier is used.

The rest of this paper is organized as follows. The related works is presented in Section 2. Section 3 introduces preprocessing of ECG signals and two feature extraction algorithm. The two hierarchical classification structure is explained in Section 4. We give the experiment results in Section 5. Finally, our paper is ended with the concluding remarks in Section 6.

2. RELATED WORKS

Automatic and accurate human identification systems have become increasingly important in several aspects of daily lives, such as in access control, financial transactions, electronic commerce and other. Traditional strategies to accomplish identification (e.g., "password", "IDs") are no longer adequate to satisfy modern requirements. Compared to traditional methods, biometrics features are more reliable and secure in verifying individuals. There are two main biometrics features for human identification system, which can be refer to either physiological or behavioral. Physiological biometrics features commonly include face, fingerprints, retina, iris, and etc. Behavioral biometrics features include signature, voice, and etc.

An ECG signal describes the electrical activity of the heart over time and can be recorded noninvasively using electrodes attached to the surface of the body (Silipo *et al*, 1996). Advantages of using the ECG for biometrics recognition include universality, permanence and uniqueness, robustness to attack, aliveness detection, and data minimization (Agrafioti *et al*, 2011). Previous works about feature vectors measured from different parts of ECG signals for classification can be summarized as either fiducial points dependent or independent. Fiducial point dependent methods depend on local characteristics of the heartbeat, such as time duration, or amplitude differences between fiducial points. The non-fiducial point approaches extract features statistically based on overall morphology of waveform (Agrafioti *et al*, 2011).

Biel *et al.* (2001) used an equipment called SIEMENS to transfer and convert ECG to a usable format. A feature selection algorithm based on correlation matrix is employed to reduce the dimension of features. The method used to classify persons is SIMCA (Soft Independent Modeling of Class Analogy). The SIMCA model will find similarities between test objects and classes rather than identical behavior. The experiment tested 20 persons and 100% identification rate was achieved by using empirically selected features. Lack of automatic identification is the major drawback.

Saechia *et al.* (2005) proposed a human identification system using Fourier transform of ECG signal as feature extraction tool. Once the ECG signals are normalized to be based on the same heart rate, three subsequences are divided and corresponded to P, QRS, and T waves, respectively. From the resulted Fourier coefficients, only significant elements are selected and employed in neural network for classification. Among the using database, their experiment results show that the proposed system can identify 31 strangers of 35 individuals.

Wang *et al.* (2008) presents a systematic analysis for human identification from ECG data. A fiducial-detection-based framework that incorporates analytic and appearance attributes is introduced. Existing solutions for ECG signals recognition are based on temporal and amplitude distances between detected fiducial points. Such method heavily relies on the accuracy of fiducial detection. To completely relax the detection of fiducial points, a new approach based autocorrelation in conjunction with discrete cosine transform is proposed. Two public ECG databases (PTB and MIT-BIH) are used. Experiment results show the proposed framework can achieve 100% subject/individual identification.

3. PROPOSED METHOD

Human identification is essentially a pattern recognition problem which basically involves signal preprocessing, feature extraction, and classification. ECG signal is one of the most important biometric attributes and it can be used for human identification due to the fact that different individuals have different physiological and geometrical hearts, which displays certain uniqueness in their ECG signals.

ECG signals are the recordings of the electrical activity of the heart. It can be roughly divided into phases of depolarization and repolarization (Biel *et al*, 2001). The depolarization phases correspond to the P-wave and QRS-wave. The repolarization phases correspond to the T-wave. A basic ECG signal cycle is shown in Figure 1.
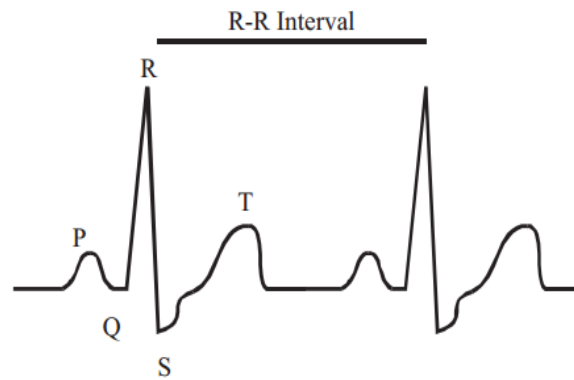
Figure 1. Basic ECG Signal Cycle

3.1 Preprocessing

The raw ECG signals usually contain low and high noise components (Israel *et al*, 2005). The low frequency noise is expressed as the slope of the overall signal across multiple heartbeat traces. The high frequency noise is expressed as the intra-beat noise. Reference (Israel *et al*, 2005) points out that three fundamental frequencies can be identified: the 60Hz electrical noise due to power line, the 1.10Hz heartbeat information and 0.06Hz change in baseline electrical potential. The remainder of the frequency is a combination of other noise source and subject information. The goal of filtering is to remove the 0.06 and 60Hz noise while retaining the individual heartbeat information between 1.10Hz and 40Hz. In this system, Butterworth band-pass filter is selected to perform noise filtering. The cutoff frequencies of the filter is 1Hz-40Hz based on empirical results.

Noise filtering preprocessing of ECG signal is to minimize the negative effects of noises. Figure 2 gives a graphic illustration of the applied preprocessing procedure.
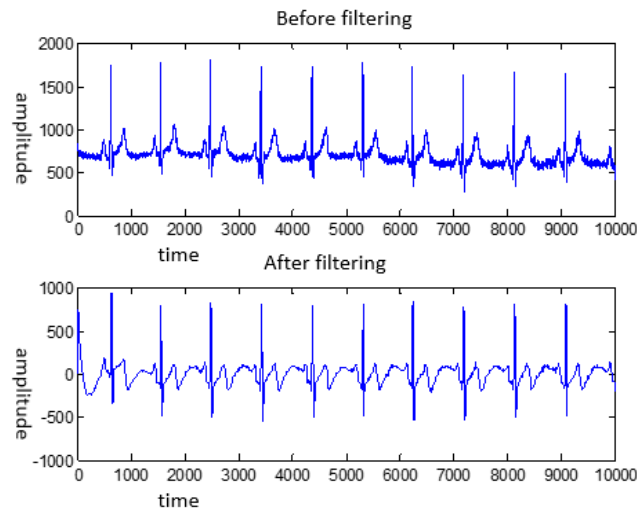

Figure 2. ECG signal preprocessing

3.2 Global Shape Feature

The ECG is non-periodic but highly repetitive signal. For one same person, the shape of R-R intervals of ECG signal is nearly the same. But for different people, the shape of R-R intervals is also some kind different. Global shape features are extracted based on this attribute. After preprocessing of one ECG signal,

R points are found in the signal, and then ten R-R intervals are cut from the ECG signal to average into one interval.

Assume one person has n normal R-R intervals denoted as $S = \{S_1, S_2, S_3, \ldots, S_n\}$, then the average R-R length of these n normal R-R intervals calculated and denoted as $\mu = \sum_{i=1}^{n} |S_i|/n$, where $|S_i|$ is the length of S_i. If $|S_i| > \mu$, this R-R interval should be compress and the position of deleting point is at $\lfloor |S_i|/(|S_i| - \mu) + 1 \rfloor$; if $|S_i| < \mu$, this R-R interval should be fill with mean value of two points and one point is right before the position $\lfloor |S_i|/\mu - (|S_i|) + 1 \rfloor$ and one is right after the position. Make sure length of all the n R-R intervals are equal to μ now. We get the global shape feature G by $G_i = \sum_{j=1}^{n} S_{ij}$, where i=1, 2, 3,…., μ. Figure 3 shows the basic diagram of global shape feature extraction.
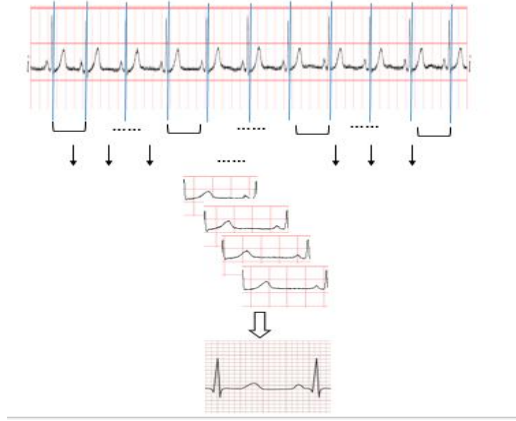

Figure 3. Diagram of global shape feature extraction

3.3 Local Statistical Feature

Local statistical feature are extracted based on statistical counting and ranking of binary patterns that converted by ECG signal samples. According to (Fufu and Tseng, 2012), some advantages of statistical based algorithm are: there is no need for QRS detection while running the algorithm and the result may still be robust to dynamic variation of ECG signals; variations of the length and the sampling rate of matching signals are allowed; the algorithm performs rapidly with low computational complexity.

Consider ECG signal as $S = \{x_1, x_2, \ldots x_i, \ldots x_n\}$, where x_i corresponds to the i_{th} input data. An interval-distance-set between x_i and x_j is denoted as $I = \{I_1, I_2, \ldots \ldots I_l\}$, where all I_i in I is integer and represent as a distance. According to interval-distance-set, compare each pair of consecutive input signals and categorise the data into one of the two cases: a decrease or increase in x_i. A preliminary reduced function then maps these two cases to 0 or 1, respectively, according to (1):

$$y_i = \begin{cases} 0, x_{i+Ip} \leq x_i, 1 \leq i \leq n \\ 1, x_{i+Ip} > x_i, 1 \leq p \leq l \end{cases} \quad (1)$$

Equation (1) converts the ECG signal of length n to a binary sequence $Y = \{y_1, y_2, \ldots y_{n-1}\}$ of length $n-1$. Group every m in Y into a rank order binary sequence of length m, referred to as an m-bit word; collect all such words to form a rank order binary pattern $B = \{b_1, b_2, . b_k, \ldots b_{n-m}\}$ where $b_k = \{y_k, y_{k+1}, \ldots, y_{k+m-1}\}$. We then convert each m-bit word b_k to its decimal expansion w_k. Next, count the occurrences of all w_k and sort them in order of descending frequency. For $k = 1, 2, \ldots, n-m$, define $j = w_k$. It is obvious that values of j range from 0 to 2^m-1 Let $p(j)$ be the corresponding relative frequency of j, $p(j) = n_j/(n-m)$ and $\sum_{j=0}^{(2^m-1)} n_j = n - m$, and it is the local statistical feature.

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4. HIERARCHICAL CLASSIFICATION STRUCTURE

Global shape features and Local statistical features are two complementary representations of the characteristics of the ECG signals. An efficient integration of these two kinds of features will enhance the identification performance.

4.1 Back Propagation Neural Network

Back propagation, an abbreviation for "backward propagation of errors", is a common method of training artificial neural networks. The BPNN (Back Propagation Neural Network) algorithm learns the weights for a multilayer network, given a network with a fixed set of units and interconnections. It employs gradient descent to attempt to minimize the squared error between the network output values and the target values for those outputs.

Each training example is a pair of the form $<\vec{x},\vec{t}>$, where $\vec{x}$ is the vector of network input values, and $\vec{t}$ is the vector of target network output values and η is the learning rate(e.g., 0.05). We denoted n_{in} as the number of network input, n_{hidden} the number of units in the hidden layer, and n_{out} the number of output units. The input from unit i into unit j is denoted x_{ji}, and the weight from unit i to unit j is denoted w_{ji}. First we create a feed-forward network with n_{in} inputs, n_{hidden} hidden units, and n_{out} output units. Initialize all network weights to small random numbers. For each $<\vec{x},\vec{t}>$ in training examples, we do propagate the input forward through the network: Input the instance $\vec{x}$ to the network and compute the output o_u of every unit u in the network. The sigmoid unit first computes a linear combination of its inputs, and then applies a threshold to the result. In the case of the sigmoid unit, however, the threshold output is a continuous function of its input. More precisely, the sigmoid unit computes its output o as $o = \sigma(\vec{w} \bullet \vec{x})$ where $\sigma(y) = 1/(1 + e^{-y})$. Then propagate the errors backward through the network. For each network output unit k, calculate its error term $\delta_k = o_k(1 - o_k)(t_k - o_k)$. For each hidden unit h, calculate its error term $\delta_h = o_h(1 - o_h)\sum_{k \in outputs} w_{kh}\delta_k$, then update each network weight $w_{ji} = w_{ji} + \Delta w_{ji}$ where $\Delta w_{ji}(n) = \eta\delta_j x_{ji} + \alpha\Delta w_{ji}(n-1)$. This is called adding momentum, which is a common way in weight-update rule.

4.2 Genetic Algorithm Based on Back Propagation Neural Network (GA-BPNN)

In recent years, genetic algorithm based on artificial neural network model as an objective or fitness function has been applied successfully in optimizing the input space of various bioprocess studies (Zhang *et al,* 2007). Genetic algorithm is an artificial intelligence-based stochastic non-linear optimization technique which solves optimization problems based on natural selection, the process that drives biological evolution. Using genetic algorithm is capable of finding both the weights and the architecture of a neural network, including number of layers, the processing elements per layer and the connectivity between processing elements.

4.3 Hierarchical Classification Structure

To better utilize the complementary characteristics of global shape feature and local statistical feature, a two hierarchical classification structure have been adopted mainly spired by the idea of changing large class number problem to small class number problem. In pattern recognition, when the number of classes is large, the boundaries between different classes tend to be complex and hard to separate. It will be easier if we can reduce the possible number of classes and perform classification in a smaller scope (Wang *et al,* 2008). Using a hierarchical architecture, we can first classify the input into a few potential classes, and a second-level classification can be performed within these candidates.

Figure 4 is the basic chart of the two hierarchical architectures. In the first step, we could use the global shape feature for classification using GA-BPNN. During this step, most unrelated subjects are filtered. If all the test samples can be classified as one subject, then the first GA-BPNN classifier can output this result directly. Otherwise, the local statistical features for classification using GA-BPNN filters the rest subjects.

This classification structure maps global classification into local classification and reduces the complexity and difficulty. Such hierarchical architecture can be applied to other pattern recognition problems as well.
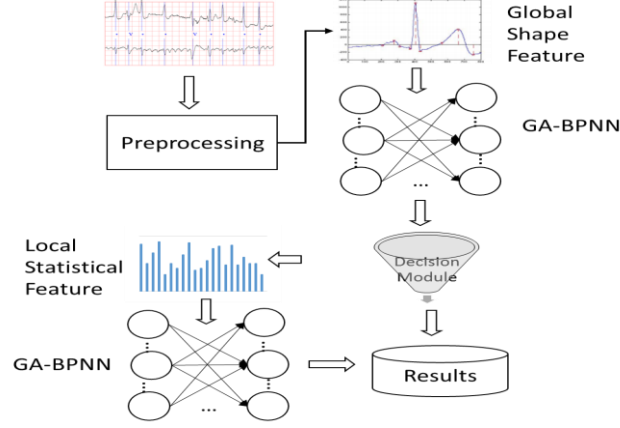

Figure 4. Hierarchical Classification Structure

5. EXPERIMENT AND RESULT

To evaluate the performance of our proposed methods, we conducted our experiments on two sets of public databases: PTB (Bousseljot *et al*, 1995) and MIT-BIH (Goldberger *et al*, 2000). The PTB database is offered from the National Metrology Institute of Germany and it contains 549 records from 294 subjects. Each record of the PTB database consists of the conventional 12-leads and 3 Frank leads ECG. The signals were sampled at 1000 Hz with a resolution of 0.5μV. The criteria for data selection are healthy ECG waveforms and at least two recordings for each subject. We randomly select 38 subjects from the total 294 subjects. The MIT-BIH Normal Sinus Rhythm Database contains 18 ECG recordings from different subjects. The recordings of the MIT database were collected at the Arrhythmia Laboratory of Boston's Beth Israel Hospital. The MIT- BIH Normal Sinus Rhythm Database was sampled at 128 Hz.

We design our experiment by using nearest neighbor (NN) classifier, GA-BPNN, and hierarchical classifier, respectively. Either global shape feature or local statistical feature is used for single classifier. Combined those two features can work as a hierarchical classifier. In the Figure 5, G/L-NN represent for global shape feature/local statistical feature for NN classifier; G/L-GABPNN represent for global shape feature/local statistical feature for GA-BPNN; NN+GABPNN represent for using hierarchical structure with global shape feature for NN classifier and local statistical feature for GA-BPNN.

Experiment results show that for 38 subjects of PTB with identification accuracy rate 97% and 18 subjects of MIT-BIH with identification accuracy rate 100%. Both are get their best result when using hierarchical classification structure.

While compared to other similar methods, experiment results of the method we proposed show it can achieve reliable identification accuracy. The RBP method (Fufu and Tseng, 2012) can reach 95.791% in the identification accuracy at its best. The RBP method is similar to the local statistical feature extraction process and the difference is that we use a set of intervals other that the interval 1. In (Fufu and Tseng, 2012), a weighted distance formula (2) is defined to measure the similarity of two ECG signals:

$$D_m(S_1, S_2) = \frac{\sum_{k=0}^{(2^m-1)} | R_1(w_k) - R_2(w_k) | \, p_1(w_k) p_2(w_k)}{(2^m - 1) \sum_{k=0}^{(2^m-1)} p_1(w_k) p_2(w_k)} \qquad (2)$$

where $p_i(w_k)$ and $R_i(w_k)$ represent the probability and ranking of w_k in the sequence S_i, $i =1$ or 2. The absolute difference between two rankings is multiplied by the normalized probabilities as a weighted sum; the factor 2^m-1 in the denominator is to ensure all values of D_m lie between 0 and 1.

The AC/DCT method (Wang *et al, 2008*) is a similar hierarchical classification structure using LDA classifier and nearest neighbor classifier. Wang *et al* (2008) proposed a feature extraction method without fiducial detection based on a combination of autocorrelation and discrete cosine transform. The AC/DCT method involves four stages: (1) windowing, where the preprocessed ECG trace is segmented into non-overlapping windows, with the only restriction that the window has to be longer than the average heartbeat length so that multiple pulses are included; (2) estimation of the normalized autocorrelation of each window; (3) discrete cosine transform over L lags of the autocorrelation signal; and (4) classification based on significant coefficients of DCT. The AC/DCT method offers 94.47% and 97.8% window recognition rate for the PTB and MIT-BIH datasets, respectively. The comparison is shown as Figure 6.
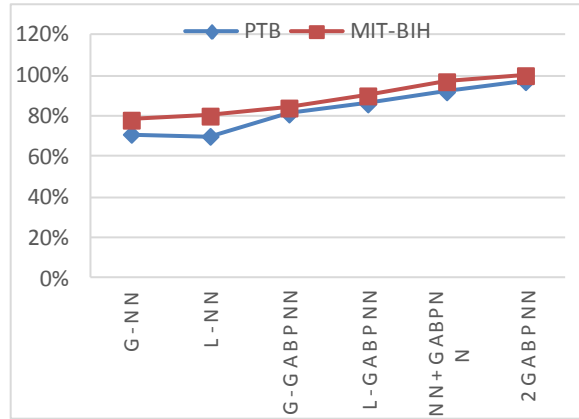

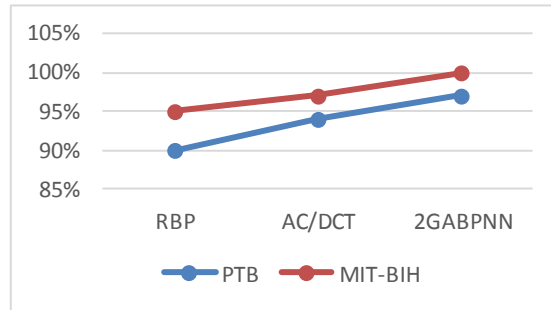Figure 5. Comparison of experiment results

Figure 6. Comparison with other methods

6. CONCLUSION

This paper proposes a human identification system using global shape features and local statistical feature of ECG signals. The global shape features are extracted based on the characteristic of non-periodic but highly repetitive of ECG signals. Differences in the shape of their ECG signals between different individuals indeed exist. The local statistical features taking the advantage of local difference among samples in one signal. To better utilize the complementary characteristic of local statistical features and global shape features, a two hierarchical classification structure has been adopted, which is mainly spired by the idea of changing large class number problem to small class number problem. Experiment results show the two combined GA-BPNN classifier achieved better identification accuracy for both PTB and MIT-BIH databases. The idea of global feature combines local feature and using a hierarchical classification can be referenced by identification system using other biometric features.

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