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Combining Independent Component Analysis and Backpropagation Neural Network for ECG Beat Classification

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Abstract—**We propose a method that uses independent component analysis (ICA) and backpropagation neural network to classify electrocardiogram (ECG) signals. In this study, ICA is used to extract important features from ECG signals. A backpropagation neural network follows to classify the input ECG beats into one of eight beat types. The independent components are calculated from the training ECG beats and serve as the ICA bases of the system. The ECG beat samples are then projected on the bases to build the ICA features for different beat types. The features based on ICA and the time interval between successive ECG beats are constituted into a feature vector and serve as inputs to the backpropagation neural network. In the study, 9800 QRS samples, including eight different ECG types, were extracted from the MIT-BIH arrhythmia database for experiments. Half of the samples were used in the training phase and the other half in the testing phase. The experiments showed an impressive highest accuracy of 98.37% under the condition that only 23 independent components were used. The results demonstrate the capability of the proposed method in the computer-aided diagnosis of heart diseases based on ECG signals.**

I. INTRODUCTION

THE electrocardiogram (ECG) has become one of the most important tools in the diagnosis of heart diseases because it is noninvasive in nature and abundant in diagnostic information. Early and quick detection and classification of ECG arrhythmia is important, especially for the treatment of patients in the intensive care unit. This requisite gives rise to the recent intensive studies in developing computer-aided diagnostic systems based on ECG. The capability of a computer-aided diagnostic system depends on its ability to discriminate the various ECG types based on their morphological features. In this study, we propose to use independent component analysis (ICA) method to extract features from the ECG beats. These ICA features together with the RR interval then serve as inputs to a backpropagation neural network classifier to separate the ECG signals into different pathological types.

Independent component analysis (ICA) [1]-[3] is an effective statistical technique developed originally to deal with problems that are related to the cocktail-party problem. This technique expresses a set of random variables as linear combinations of random variables that are statistically mutually independent. ICA is mainly applied to solve problems such as blind source separation (BSS) and feature extraction. The application of ICA to biomedical signal analysis includes, but is not limited to, the separation of fetal and maternal ECG signals [4], blind Electrogastrogram (EGG) separation [5], EEG and MEG recordings analysis [6], and the characterization of ECG signals [7].

In the application of ICA to ECG signals, Owis et al. used ICA to calculate the components in the Fourier transformed domain that are statistically mutual independent [7]. The features were calculated by projecting the ECG signals onto the subspace constituted by the independent components (ICs). By using the ICA-based features to classify five ECG beat types, they attained a high accuracy of 100% in classifying normal beats, under the condition that more than 219 ICs should be used. However, the accuracies in discriminating the other arrhythmias were moderate. Carefully inspecting the spectra of different ECG beats, we discovered that three out of the five types of arrhythmias have similar spectral density, which could be the reason that causes the misclassification. Moreover, the large number of ICs can cause the calculation burden in the training stage when large database is used.

In this study, we intend to classify eight ECG beat types, including the normal rhythm and seven arrhythmias, with combined ICA features and a backpropagation neural network. The important features of the ECG signals are extracted by applying ICA in the time-domain. The ICA features together with the RR interval then serve as inputs to the following backpropagation neural network for classification. Experiments are designated to evaluate the capability of the system.

II. METHOD

We assumed that the ECG signal is composed of the weighted sum of a set of basic components. These basic components could be estimated with blind source separation method such as independent component analysis (ICA). In this section, we first give a short introduction of the independent component analysis (ICA) method and then describe the proposed method of our system in details.

A. Independent component analysis (ICA)

Independent component analysis (ICA) is a signal processing technique whose goal is to express a set of random variables as linear combinations of statistically independent component variables [3]. Assume that at time instant t the observed m random variables $x_1(t), \ldots, x_m(t)$, are modeled as linear combinations of n random variables $s_1(t), \ldots, s_n(t)$.

Using the vector-matrix notation, the mixing model is written as

$$\mathbf{x(t)} = \mathbf{As(t)}, \tag{1}$$

where $\mathbf{x}(t)=[x_1(t), \ldots, x_n(t)]^T$, $\mathbf{s}(t)=[s_1(t), \ldots, s_m(t)]^T$; the elements a_{ij}, (i=1, ..., m, j=1, …,n) in matrix **A** are some real coefficients. The signals s_1 (t), …, s_n(t), are called the source signals and are supposed to be mutually independent. Since both the independent components in **s**(t) and the coefficients of the mixing matrix **A** are unknown, the aim of ICA is to estimate both unknowns from the observed **x**(t) with appropriately statistical assumptions on the source distributions.

The initial step to estimate the ICA bases is whitening or sphering which is a transformation such that the measurements are made uncorrelated and unit-variance [3]. The whitening could be accomplished by principal component analysis (PCA) that the data are described by the coefficients of a predetermined orthogonal set. In the whitening process, the whitened data **z** is defined by $\mathbf{z} = \mathbf{Vx}$, with $E\{\mathbf{zz}^T\} = \mathbf{I}$, where **I** is the identity matrix. The whitening matrix **V** is given by $\mathbf{V} = \mathbf{UD}^{-1/2}\mathbf{U}^T$, where **D** is a diagonal matrix with eigenvalues of the covariance matrix $E\{\mathbf{x}(t)\mathbf{x}(t)^T\}$, and **U** is a matrix with the corresponding eigenvectors in its columns.

With the transformation with PCA, the model in (1) can be expressed as

$$\mathbf{z} = \mathbf{VAs} = \mathbf{Bs}. \tag{2}$$

Since matrix **B** is orthogonal, the solution of independent sources can be written in the form

$$\hat{\mathbf{s}}\mathbf{(t)} = \mathbf{B}^T\mathbf{z(t)}. \tag{3}$$

The basic works to estimate the independent components (ICs) rely on measuring the non-Gaussianity of different vectors within the subspace of the whitened signals. The maximization of the non-Gaussianity leads to the identification of non-Gaussian components or independent components [3]. There are a number of algorithms for performing ICA. In this study, a fixed-point algorithm with contrast function $G(u)=log(cosh(u))$ was used to estimate independent components [2].

In the estimation of independent components, it is necessary to orthogonalize the solution vectors after each iteration, in order to retain the orthogonality. This procedure can be accomplished by using the Gram-Schmidt orthogonalization method and the independent components are estimated one after another.

B. The proposed method

The block diagram of the proposed method for ECG classification is depicted in Fig. 1. The method is divided into three steps: 1) signal preprocessing, 2) feature extraction, and 3) backpropagation neural network classifier, which are described, separately, as follows.

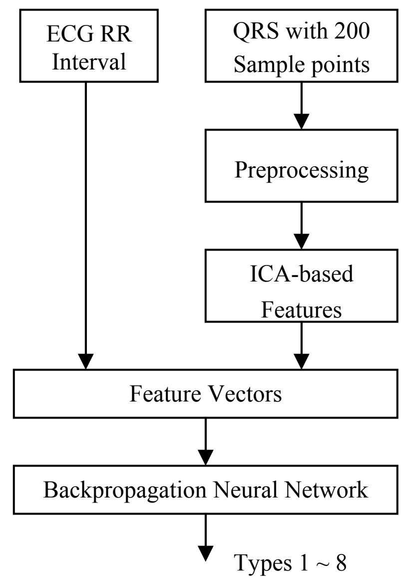

Fig. 1 Block diagram of the proposed method

1) Signal preprocessing

In this study, the ECG signals are obtained from the MIT-BIH arrhythmia database for recognition. Since most of the diagnostic information lies around the R peak of the ECG signal, hence a portion of signal before it and a portion of signal after it are selected for processing. Herein, the samples extracted from the ECG signals are 0.556 sec QRS segments with 0.278 sec data lengths both before and after the R point, resulting in 200 points in each sample at a sampling frequency of 360 Hz. Each sample is preprocessed by firstly removing the mean value to eliminate the offset effect, and then dividing with the standard deviation. This process results in normalized signals with zero mean and unity standard deviation, which aims to reduce the possible false decisions due to signal amplitude biases resulting from instrumental and human differences.

2) Feature extraction

To estimate the independent components (ICs), we randomly select two samples from each of the 50 different records selected from the MIT-BIH database, resulting in totally 100 sample segments. In the sequel, a data matrix at size 100×200 is constructed for the estimation of the ICs. The ICs are calculated using the fast ICA algorithm [2]. The ECG sample segments are then projected onto the ICs and the ICA features are calculated.

In addition to the ICA features acquired from projecting the signal on the ICA bases, the RR interval is considered as another feature. The RR interval is defined as the time elapse between successive ECG beats, which plays an important role in characterizing certain ECG types. Herein the RR interval is calculated as the time difference between the R points of the present and previous beats. The R-peak information can be

Table 1 Records and number of ECG samples used in this study. N: normal beat, L: left bundle branch block beat, R: right bundle branch block beat, A: atrial premature beat, V: premature ventricular contraction, P: paced beat, I: ventricular flutter wave, and E: ventricular escape beat.

Type	MIT-BIH data file	Training (samples/file)	Testing (samples/file)
N	100, 101, 103, 105, 108	100	100
	112, 113, 114, 115, 117	100	100
	121, 122, 123, 202, 205	100	100
	219, 230, 234	100	100
L	109, 111, 207, 214	100	100
R	118, 124, 212, 231	100	100
V	106, 119, 200, 203, 208	100	100
	213, 221, 228, 233	100	100
	116	54	54
	201	98	98
	210	96	96
	215	82	82
A	209, 222, 232	100	100
	220	47	47
	223	35	35
P	102, 104, 107, 217	100	100
I	207	236	236
E	207	52	52
Total		4900	4900

found in the annotation files of the records in the MIT-BIH database. The ICA features and the RR interval are then built into a feature vector and serve as inputs to the backpropagation neural network for classification.

3) Backpropagation neural network classifier

The backpropagation neural network [8] used in this study is a three-layer feedforward structure. In the structure, the first layer contains the same number of neurons as that of the ICA features and RR interval, the second layer have 40 neurons, and the output layer has eight neurons, which is equal to the number of ECG types to be classified.

There are three commonly used activation functions in the backpropagation multiplayer neural network, namely the logistic function, hyperbolic tangent function, and identity function [8]. In this study, the hyperbolic tangent functions are used in the first and second layers, and the identity function is employed in the output layer. The weight and bias values in the neural network are updated by Levenberg-Marquardt optimization method [8] with a learning rate of 0.1. A criterion of 0.01 in the mean-square-error is empirically determined to terminate the iterations in the training phase of the classifier.

III. Result and Discussion

A total of 9800 sample segments attributing to eight ECG beat types was selected from the MIT-BIH arrhythmia database for experiments. The eight beat types employed in this study are normal beat (N), left bundle branch block beat (L), right bundle branch block beat (R), atrial premature beat (A), premature ventricular contraction (V), paced beat (P),ventricular flutter wave (I), and ventricular escape beat (E). The information about the R-peaks and RR intervals was given in the corresponding annotation files.

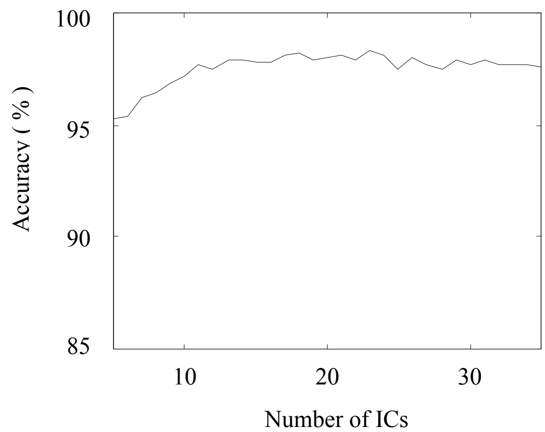

Fig. 2 Accuracy (%) versus number of ICs

The numbers and types of the ECG beat samples are summarized in Table 1, in which half of the ECG beats were selected for training and the other half for testing the classifiers.

The performances of the classification are expressed in terms of specificity, sensitivity, and overall accuracy. The specificity is defined as the fraction of correctly classified normal rhythms. The sensitivity of an arrhythmia is defined as the fraction of that specific arrhythmia correctly classified. The overall accuracy is the fraction of the total ECG beats correctly classified.

In the estimation of ICs, we sequentially calculated 100 ICs from the 100×200 data matrix in the training phase. The first 35 ICs are exploited in this study. Experiments were developed to investigate the effects of the numbers of the ICs in the classification by varying the number from 5 to 35 in the training and testing experiments. In each experiment, the same procedures were repeated ten times and the results were averaged.

Figure 2 depicts the overall accuracy versus the number of ICs used in the classifier. The result shows that the highest accuracy of 98.37% was achieved with only 23 ICs. Further increase in IC number does not further raise the accuracy of the classifier. Rather, the accuracy moves slightly up and down because of the random order in acquiring the ICs. The specificity and sensitivities of different ECG beat types are summarized in Table 2 for comparison. The specificity and the sensitivities of all of the arrhythmias under study are high. The specificity is 99.65 %. Most of the specificities are over 96 %. Even in the arrhythmia with the lowest sensitivity, an accuracy of 90.13 % can be achieved. The high classification rates in different ECG beat types result in an impressive overall accuracy of 98.37 %.

It is also interesting to compare our method with other ECG classification systems presented in the literature. The methods from five representative studies were chosen for this comparison, including a patient-adaptable classifier using mixture of experts (MOE) [9]; discrimination of VT with Fourier-Transform neural network (FTNN) [10]; ECG recognition using fuzzy hybrid neural network (Fhyb-HOSA) [11]; Characterization of ECG based on BSS (BSS-Fourier) [7]; classification of ECG using multi-resolution analysis and neural network (DWT-NN) [12].

Table 3 summarizes the comparative results of these methods. Among the six methods, the proposed method outperforms the other methods with an impressive accuracy of 98.37 % to discriminate eight types of ECG beats. Although this comparison may be unfair because of the different numbers and types of ECG beats used in different studies, the proposed method demonstrated to be an excellent tool in the computer-aided recognition of arrhythmia beats based on ECG.

IV. CONCLUSIONS

We proposed a method that uses independent component analysis (ICA) and backpropagation neural network to classify electrocardiogram (ECG) signals. In this study, ICA is used to extract important features from ECG signals and a backpropagation neural network follows to classify the input ECG beats into one of eight beat types. The experiments showed an impressive classification accuracy of 98.37% with only 23 independent components. Further increase the number of ICs does not increase the classification accuracy. The impressive result demonstrates the capability of the proposed method in the computer-aided diagnosis of heart diseases based on ECG signals.

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Table 2 Classification results of the proposed method

Number of ICs used		23
Specificity (%)		99.65
Sensitivity (%)	L	96.25
	R	99.15
	V	98.46
	A	98.40
	P	99.38
	I	90.13
	E	91.54
Accuracy (%)		98.37

Table 3 Comparative results of different methods

Method	Number of beat types	Accuracy
Proposed	8	98.37 %
MOE [9]	4	94.0 %
FTNN [10]	3	98.0 %
Fhyb-HOSA [11]	7	96.06 %
BSS-Fourier [7]	5	85.04% (*)
DWT-NN [12]	13	96.79 %

(*) Calculated from the results in the paper with 240 ICs used.

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