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Integration of independent component analysis and neural networks for ECG beat classification

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Abstract

In this paper, we propose a scheme to integrate independent component analysis (ICA) and neural networks for electrocardiogram (ECG) beat classification. The ICA is used to decompose ECG signals into weighted sum of basic components that are statistically mutual independent. The projections on these components, together with the RR interval, then constitute a feature vector for the following classifier. Two neural networks, including a probabilistic neural network (PNN) and a back-propagation neural network (BPNN), are employed as classifiers. ECG samples attributing to eight different beat types were sampled from the MIT-BIH arrhythmia database for experiments. The results show high classification accuracy of over 98% with either of the two classifiers. Between them, the PNN shows a slightly better performance than BPNN in terms of accuracy and robustness to the number of ICA-bases. The impressive results prove that the integration of independent component analysis and neural networks, especially PNN, is a promising scheme for the computer-aided diagnosis of heart diseases based on ECG.

Keywords: Independent component analysis; RR interval; Neural network; Classification

1. Introduction

The electrocardiogram (ECG) is the recording of the electrical property of the heartbeats, and has become one of the most important tools in the diagnosis of heart diseases. Due to the high mortality rate of heart diseases, early detection and precise discrimination of ECG arrhythmia is essential for the treatment of patients. This requisite contributes to intensive studies in recent years for high-precision computer-aided diagnosis (CAD) systems for ECG. An effective CAD system requires a powerful pattern classifier as well as an elegant feature extractor that is capable of extracting important, yet usually hidden, information from the raw data. Even more important is the integration of suitable feature extractor and pattern classifier such that they can operate in coordination to make an effective and efficient CAD system.

The features regularly used in ECG beat classification can be virtually divided into categories. The features can be acquired with time domain methods (De Chazal & Reilly, 2003; Hu, Palreddy, & Tompkins, 1997; Moraes, Seixas, Vilani, & Costa, 2002), with transformation methods (Acharya et al., 2004; Al-Fahoum & Howitt, 1999; Minami, Nakajima, & Toyoshima, 1999; Prasad & Sahambi, 2003), represented as statistical measures (Osowski & Linh, 2001), etc. The integration of features from different categories was not unusual (Engin, 2004). As to the pattern classification, efforts have also been devoted to the development of suitable classifiers for different kinds of feature sets, including linear discrimination, neural networks and the mixture of experts (Al-Fahoum & Howitt, 1999; De Chazal & Reilly, 2003; Engin, 2004; Hu et al., 1997; Minami et al., 1999; Osowski & Linh, 2001).

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Independent component analysis (ICA) is a statistics method whose aim is to find from multivariate (multidimensional) data the underlying components that are statistically independent to one another (Hyvärinen, Karhunen, & Oja, 2001). The application of ICA to biomedical signal analysis includes, but is not limited to, the separation of fetal and maternal ECG signals (De Lathauwer, De Moor, & Vandewalle, 2000), blind Electrogastrogram (EGG) separation (Wang, He, & Chen, 1997), EEG and MEG recording analysis (Vigário, Särelä, Jousmäki, Hämäläinen, & Oja, 2000), and the characterization of ECG signals (Owis, Youssef, & Kadah, 2002).

In the promising work of Owis et al. (2002), ICA were applied to calculate the independent components (ICs) in the Fourier transformed domain. The ICs then serve as bases for the extraction of important features to differentiate five ECG beat types. By using the ICA-based features, a high specificity of 100% is achieved in classifying normal beats, under the condition that more than 219 ICs should be used. However, the sensitivities in discriminating the other four arrhythmias were moderate. After careful inspection of the ECG spectra, we discovered that three out of the five ECG beat types have similar spectral density, which could be the reason that causes the misclassification. Moreover, the large number (as high as 219) of ICs certainly causes the calculation burden, especially when a large database is used.

We have also explored the possibility of applying ICA in the time domain to cooperate with simple, i.e. minimum-distance and Bayes, classifiers for ECG beat classification (Yu & Chou, 2006). The capacity of ICA was confirmed in the time domain to differentiate six types of ECG beats. However, if only one bank of ICA-based features was used, equally well discrimination power can not be achieved throughout all types of ECG beats. Instead, a switchable scheme should be used, which uses RR interval as an indicator to toggle between two ICA-based features of different lengths, in order to attain equally well discrimination power across different beat types. These observations may infer that using only one bank of ICA features is not sufficient to describe both the morphology and heart rate changes in the pathological ECG beats. However, since only simpler classifiers were tested in that study, we are curious whether other classifiers can cooperate with ICA in a more elegant manner.

In this study, we evaluate the integration of independent component analysis and neural network classifiers to discriminate eight types, instead of six in the earlier study (Yu & Chou, 2006), of ECG beats. Only one bank of independent components is calculated in the time domain and serves as bases to constitute the subspace for ECG signal representation. Two different neural networks, including a probabilistic neural network and a back-propagation neural network, are employed in this study. The capabilities of the neural networks in coordinate with the ICA features are justified.

2. 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. 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 (Bell & Sejnowski, 1995; Cardoso & Laheld, 1996; Comm, 1994; Hyvärinen, 1999; Hyvärinen et al., 2001)

$$\mathbf{x} = \mathbf{A}\mathbf{s}, \tag{1}$$

where $\mathbf{x}(t) = [x_1(t), \ldots, x_m(t)]^{\mathrm{T}}$, $\mathbf{s}(t) = [s_1(t), \ldots, s_n(t)]^{\mathrm{T}}$, and $\mathbf{A}$ is the mixing matrix with real coefficients a_{ij}, $(i = 1, \ldots, m; j = 1, \ldots, n)$. Since both $\mathbf{s}(t)$ and $\mathbf{A}$ are unknown, the aim of ICA is to estimate both unknowns from the observed $\mathbf{x}(t)$ with the assumption that the source signals $s_1(t), \ldots, s_n(t)$ are mutually independent.

The initial step to estimate the ICs is whitening (or sphering) which is a transformation such that the measurements are made uncorrelated and unit-variance (Hyvärinen et al., 2001). The whitening could be accomplished by principal component analysis (PCA). The whitened data $\mathbf{z}$ is defined by $\mathbf{z} = \mathbf{V}\mathbf{x}$, with $E\{\mathbf{z}\,\mathbf{z}^{\mathrm{T}}\} = \mathbf{I}$, where $\mathbf{V}$ is the whitening matrix and $\mathbf{I}$ is the identity matrix. The whitening matrix $\mathbf{V}$ is given by $\mathbf{V} = \mathbf{U}\mathbf{D}^{-1/2}\mathbf{U}^{\mathrm{T}}$, where $\mathbf{D}$ is a diagonal matrix with eigenvalues of the covariance matrix $E\{\mathbf{x}(t)\mathbf{x}(t)^{\mathrm{T}}\}$, and $\mathbf{U}$ is a matrix with the corresponding eigenvectors as its columns. With the signal model defined in (1), the whitened data $\mathbf{z}$ can be expressed as

$$\mathbf{z} = \mathbf{V}\mathbf{A}\mathbf{s} = \mathbf{W}\mathbf{s}. \tag{2}$$

Since matrix $\mathbf{W}$ is orthogonal, the solution of independent sources can be expressed as

$$\mathbf{s} = \mathbf{W}^{\mathrm{T}}\mathbf{z}. \tag{3}$$

There are a number of algorithms for performing ICA. In this study, a fixed-point algorithm with nonlinearity function $g(u) = tanh(u)$ was adopted to estimate the independent components (Hyvärinen, 1999). By using this method, the Gram-Schmidt orthogonalization procedure is used and the independent components are generated one after another.

3. Proposed methods

The block diagram of the proposed method for ECG beat classification is depicted in Fig. 1. The method is divided into three steps: (1) ECG sampling and preprocessing, (2) calculation of feature vector, and (3) classification by neural networks, which are described, separately, as follows.

3.1. ECG sampling and preprocessing

The ECG signals are obtained from the MIT-BIH arrhythmia database for recognition. Since most of the

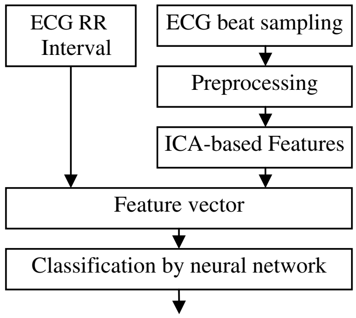

Fig. 1. Block diagram of the proposed scheme for ECG beat classification.

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 s QRS segments with 0.278 s 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.

3.2. Calculation of feature vector

Two sets of features are to be extracted from the data files. One set is the ICA-based features and the other is the RR interval. To estimate the ICA-based features, the independent components (ICs) should be calculated as bases for signal decomposition. First of all, two sample segments, each with 200 data points, are randomly selected from each of the 50 records. The sample segments are whitened and arranged into a 100×200 data matrix. The ICs are then calculated sequentially from the data matrix by using the fixed-point fast-ICA algorithm (Hyvärinen, 1999). In the sequel, the ECG signals are projected onto the bases and the features are calculated.

In addition to the ICA-based features, the interval between successive QRS peaks, the RR interval, is another important feature for characterizing many ECG arrhythmias. The RR interval is calculated as the time elapse between successive R peaks, whose information can be found in the annotation files 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 following neural network classifiers.

3.3. Classification by neural networks

The probabilistic neural network (PNN) used in this study has a two-layer structure, including a radial basis layer and a competitive layer (Mathworks Inc., 1998; Wasserman, 1993). The radial basis layer contains the same number of neurons as that of the classes to be classified. Each neuron is responsible to calculate the probability that an input feature vector is associated with a specific class. With an input vector $\mathbf{p}$, the radial basis neuron compares it with the neuron weight $\mathbf{w}$ and multiplies with a bias b to calculate the probability:

$$Y = \exp(-n^2), \tag{4}$$

where $n = \|\mathbf{w} - \mathbf{p}\| \cdot b$ and $\| \cdot \|$ denotes the Euclidean distance. Consequently, as the distance between $\mathbf{w}$ and $\mathbf{p}$ decreases, the output increases and reaches the maximum of 1 when $\mathbf{w} = \mathbf{p}$. The bias b is set as (Mathworks Inc., 1998)

$$b = \sqrt{-\ln(0.5)}/\text{spread}, \tag{5}$$

such that the probability crosses 0.5 when $\|\mathbf{w} - \mathbf{p}\| = \text{spread}$. The sensitivity of the radial basis neurons can be adjusted by varying the value of b through the coefficient spread. In the study, we empirically determine the value of spread as 0.9 that produces satisfactory results. The competitive layer then determines the maximum in the probabilities and assigns 1 to the associated class and 0 for the other classes.

On the other hand, the back-propagation neural network (BPNN) used in this study is a three-layer feed-forward structure (Jang, Sun, & Mizutani, 1997). The first layer is the input layer that has the ICA features and the RR interval as inputs. The second layer, also called the hidden layer, has 40 neurons and the output layer has eight neurons, which is equal to the number of ECG beat types to be classified. There are three commonly used activation functions for the back-propagation multiplayer neural network, namely the logistic function, hyperbolic tangent function, and identity function. In this study, the hyperbolic tangent functions are used in the first and second layers, and the identity function is used in the output layer. The weight and bias values in the BPNN are updated by Levenberg-Marquardt optimization method (Jang et al., 1997) with a learning rate of 0.1. A criterion of 0.01 in mean-square-error is empirically determined to terminate the iterations in the training phase of the classifier.

3.4. Performance evaluation

The performances of the classification are evaluated in terms of sensitivity, specificity, and overall accuracy. The sensitivity is calculated as the fraction of correct classifying an abnormal beat when there is actually an arrhythmia. The specificity is the fraction of correct classification of the normal rhythm. The overall accuracy is the fraction of the total number of beats correctly classified.

4. Experiment and result

A total of 9800 sample segments attributing to eight ECG beat types were selected from the MIT-BIH arrhythmia database for experiments. The eight beat types employed in the study were normal beat (NORM), left bundle branch block beat (LBBB), right bundle branch block beat (RBBB), artial premature beat (APB), premature ventricular contraction (PVC), paced beat (PB), ventricular flutter wave (VFW), and ventricular escape beat (VEB). The types and numbers of the ECG beats exploited in the study are summarized in Table 1, in which half of the ECG beats were selected for training and the other half for testing the classifiers. Each sample is a 0.556 s QRS segment with 0.278 s of signal both before and after the R point, resulting in 200 points at a sampling frequency of 360 Hz. The associated RR interval was calculated from the locations of the R points documented in the annotation files of the MIT/BIH database.

In the estimation of ICs, we randomly select two samples from each of the records in the database. In the sequel, the selected samples constitute a 100×200 data matrix. We then sequentially calculated the ICs from the 100×200 data matrix with the fast-ICA algorithm (Hyvärinen, 1999), resulting in totally 100 ICs. The first 20 ICs were plot in Fig. 2. To study the effect of IC numbers to the differentiation of the eight ECG beat types, we varied the numbers of ICs from 5 to 50 and their effects were justified. Since the fast-ICA algorithm calculates the ICs in an arbitrary order, we repeated each of the experiment setups for 10 times and the results were averaged.

The average accuracy versus the number of ICs used for the PNN and BPNN are depicted in Figs. 3 and 4, respectively. In Fig. 3, the discrimination power of PNN, revealed as the average accuracy, increases rapidly at small numbers of ICs and then reaches a plateau at around 33 ICs. At even higher IC numbers, the average accuracies stay at around 98.7%. Further increase in IC number does not significantly increase the accuracy of the classifier. On the other hand, in Fig. 4 the BPNN classifier shows a fluctuated response. The

Table 1
Records and number of ECG samples used in this study

Type	MIT-BIH data file	Training (#/file)	Testing (#/file)
NORM	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
LBBB	109,111,207,214	100	100
RBBB	118,124,212,231	100	100
PVC	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
APB	209,222,232	100	100
	220	47	47
	223	35	35
PB	102,104,107,217	100	100
VFW	207	236	236
VEB	207	52	52
Total		4900	4900

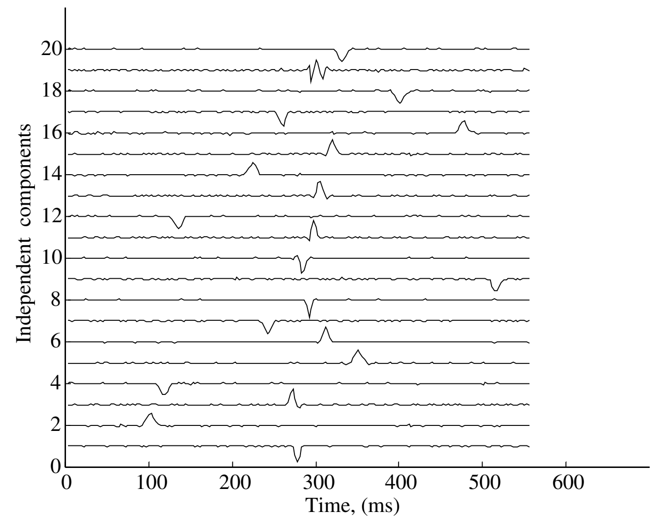

Fig. 2. The first 20 independent components.

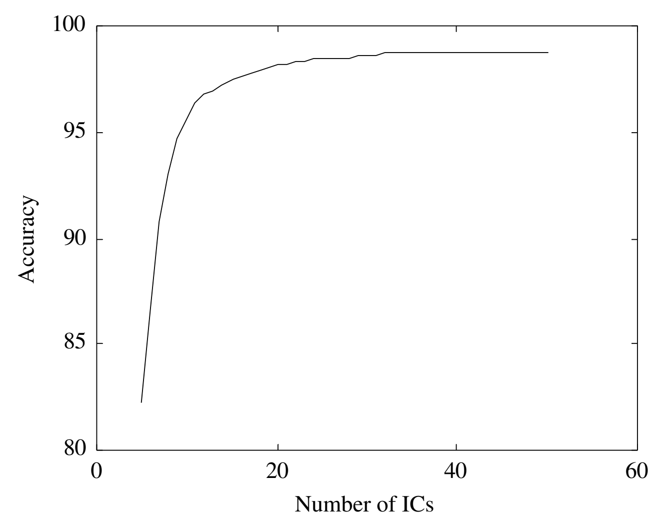

Fig. 3. Average accuracy (%) versus number of ICs with PNN.

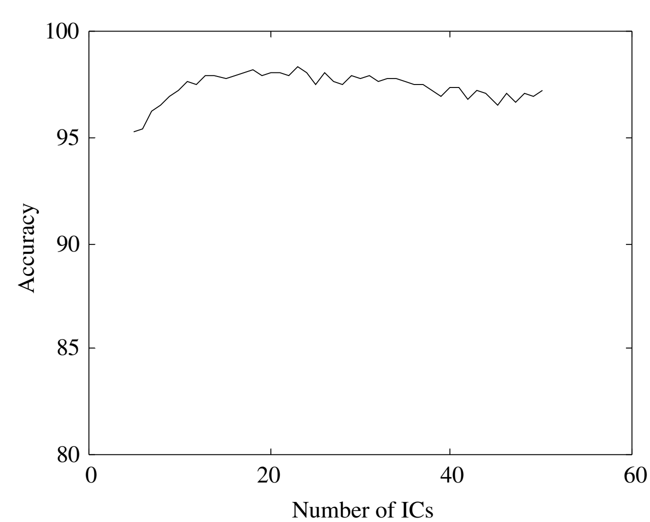

Fig. 4. Average accuracy (%) versus number of ICs with BPNN.

Table 2
Classification results of the proposed scheme with BPNN and PNN classifiers

IC number		BPNN classifier		PNN classifier	
		23		33	
		Mean	Std	Mean	Std
Specificity (%)	NORM	99.650	0.106	99.906	0.061
	LBBB	96.250	1.658	99.650	0.122
	RBBB	99.150	0.673	99.975	0.075
	PVC	98.455	0.415	98.016	0.186
Sensitivity (%)	APB	98.403	0.475	98.508	0.537
	PB	99.375	0.464	100.000	0.000
	VFW	90.127	3.073	88.898	1.225
	VEB	91.538	2.609	92.885	0.881
Accuracy (%)		98.367	0.235	98.710	0.082

highest average accuracy of 98.37% is reached at 23 ICs. Further increase in IC number does not necessary increase the accuracy of the classifier. Instead, the average accuracy fluctuates all the way throughout all the testing IC numbers.

The specificity and sensitivities of the two neural network classifiers are summarized in Table 2, in which the optimal numbers of the ICA-bases were used, i.e. 33 and 23 for PNN and BPNN, respectively. It is impressive to find that both classifiers demonstrate high specificities of over 99.65%. Moreover, most of the sensitivities with both classifiers are over 98%, with relatively small value of standard deviation. The overall accuracy achieves a high value of 98.710% (with standard deviation of 0.082%) by using PNN and 98.367% (with standard deviation of 0.235%) by using BPNN. Please note that the number of IC bases need to attain this high accuracy are only 33 and 23 for PNN and BPNN, respectively, both of which are substantially lowered than that in the other methods (e.g. 219 ICs in Owis et al., 2002). For the items that show lower sensitivities, PNN outperforms BPNN in LBBB and VEB, yet depicts minor inferior to BPNN in VFW. Since both VFW and VEB contain relatively small numbers of samples (see Table 1), we may consider the major difference would be in the recognition of LBBB, in which PNN outperforms BPNN.

5. Discussions

Comparing the average accuracy achieved with the two neural network classifiers depicted in Table 2, the result reveals that the integration of ICA with PNN classifier has a slightly better performance than that with BPNN classifier. This superiority is augmented when we also consider the smoother response to the IC numbers with PNN in Fig. 3 than that with BPNN in Fig. 4. The averaging process by repeating the same experiments for 10 times results in a smooth response on the PNN while still demonstrating fluctuations with BPNN. Since the standard deviation of the accuracies achieve by both classifiers are low, we infer that the order of ICA bases has minor effect on the fluctuation. Rather, the random initial weights assigned to the BPNN in each of the training phases should be responsible for the fluctuation, since different initial values could result in different classification results. This observation also demonstrated the relative higher robustness to ICA-bases with PNN than with BPNN.

For a real-world ECG classification system, an R-wave detector should be included into the system as a preprocessor. Errors result from the R-wave detector may degrade the performance of the classifier. Fortunately, a number of schemes have been published in the literature which claimed impressively high detection rate of more than 99.5% for the R-waves (Afonso, Tompkins, Nguyen, & Luo, 1999; Lagerholm, Peterson, Braccini, Edenbrandt, & Sornmo, 2000). In our scheme, we do not intend to detect the R-waves but use the information of R-waves provided in the MIT-BIH database which were manually verified by specialists.

It is also interesting to compare the result of our scheme for ECG classification with that of the other methods presented in the literature. Methods from six representative studies were chosen for this comparison, including a patient-adaptable classifier using time-domain features and a mixture of experts (MOE) (Hu et al., 1997); discrimination of VT with Fourier transform and neural network (FTNN) (Minami et al., 1999); ECG recognition using statistical features and fuzzy hybrid neural network (Fhyb-HOSA) (Osowski & Linh, 2001); characterization of ECG based on Fourier-domain BSS (BSS-Fourier) (Owis et al., 2002); classification of ECG using multi-resolution analysis and neural network (DWT-NN) (Prasad & Sahambi, 2003); ECG classification by combining three different kinds of features and neuro-fuzzy network (NFN) (Engin, 2004). Table 3 summarizes the comparative results of these methods, in which the first row of the table is the result of the method integrating ICA and PNN proposed in this paper. Among the seven methods, the proposed method outperforms the other methods with an impressive accuracy of 98.71% to discriminate eight ECG beat types. Although this comparison may not be completely fair because of the different numbers and types of ECG beats tested, the propose scheme reveals to be a powerful tool in the computer-aided diagnosis of heart diseases based on ECG.

Table 3
Comparative results of different ECG beat classification methods

Method	Number of beat types	Accuracy (%)
Proposed	8	98.71
MOE	4	94.0
FTNN	3	98
Fhyb-HOSA	7	96.06
BSS-Fourier	5	85.04[a]
DWT-NN	13	96.79
NFN	4	98

[a] Calculated from the results in the paper.

6. Conclusion

In this paper, we proposed a scheme to combine independent component analysis (ICA), RR interval, and neural network classifiers for ECG beat classification. ICA is used to extract important factors from ECG signals. The ICA-based features together with the RR interval then serve as input feature vector for the following neural network classifiers. Two neural networks, including probabilistic neural network (PNN) and back-propagation neural network (BPNN), were employed in the study and their effects were compared. Eight types of ECG samples were selected from the MIT-BIH arrhythmia database for experi- ments. Both neural network classifiers demonstrated high classification accuracies of over 98% with relatively small number of ICs. Between the two neural network classifiers, PNN shows a slightly better performance than BPNN in terms of classification accuracy and robustness to different number of ICA-bases. The results prove that the proposed scheme a promising model for the discrimination of linical ECG signals.

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