Available online at www.sciencedirect.com
ScienceDirect
Expert Systems with Applications 34 (2008) 2841–2846
Expert Systems with Applications
www.elsevier.com/locate/eswa

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

Sung-Nien Yu [a,*], Kuan-To Chou [a,b]

[a] Department of Electrical Engineering, National Chung Cheng University, 168 University Road, Ming Hsiung, Chia-Yi 621, Taiwan
[b] Department of Electronic Engineering, Wu Feng Institute of Technology, 117, Chian-Kuo Road, Sec. 2, Ming Hsiung, Chia-Yi 621, Taiwan

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).

* Corresponding author. Tel.: +886 5 2720411x33205; fax: +886 5 2720862.
E-mail address: yusn@ee.ccu.edu.tw (S.-N. Yu).

0957-4174/$ - see front matter
doi:10.1016/j.eswa.2007.05.006

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