



Detection of electrocardiogram signals using an efficient method



A. Ebrahimzadeh*, B. Shakiba, A. Khazaei

Faculty of Electrical and Computer Engineering, Babol University of Technology, Iran

ARTICLE INFO

Article history:

Received 29 January 2013

Received in revised form 29 April 2014

Accepted 1 May 2014

Available online 13 May 2014

Keywords:

ECG beat classification

Higher order statistics

Radial basis function neural network

Bees algorithm

ABSTRACT

Automatic detection of electrocardiogram (ECG) signals is very important for clinical diagnosis of heart disease. This paper investigates the design of a three-step system for recognition of the five types of ECG beat. In the first step, stationary wavelet transform (SWT) is used for noise reduction of the electrocardiogram (ECG) signals. Feature extraction module extracts higher order statistics of ECG signals in combination with three timing interval features. Then hybrid Bees algorithm-radial basis function (RBF.BA) technique is used to classify the five types of electrocardiogram (ECG) beat. The suggested method can accurately classify and discriminate normal (Normal) and abnormal heartbeats. Abnormal heartbeats include left bundle branch block (LBBB), right bundle branch block (RBBB), atrial premature contractions (APC) and premature ventricular contractions (PVC). Finally, the classification capability of five different classes of ECG signals is attained over eight files from the MIT/BIH arrhythmia database. Simulation results show that classification accuracy of 95.79% for the first dataset (4000 beats) and an overall accuracy of detection of 95.18% are achieved over eight files from the MIT/BIH arrhythmia database.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

The analysis of ECG has been extensively used for diagnosing many cardiac diseases. The development of precise and fast methods for automatic ECG classification is very important for clinical diagnosis of heart diseases.

There are several methods proposed in the literature for the purpose of automatic arrhythmia classification in ECG signals, and a typical system for such an goal can be divided into three subsequent categories (preprocessing, feature extraction, and classification) as shown in Fig. 1, in which N (normal), L (left bundle branch block), R (right bundle branch block), A (atrial premature contraction) and V (premature ventricular contraction) illustrate heartbeat classes to be analyzed in this study.

In the preprocessing step, frequencies of the ECG signal related to artifacts is detected and attenuated. Those artifacts can be from a biological source, like muscular activity, or originated from an external source, such as 50/60 Hz electric network frequency. In this study, stationary wavelet transform (SWT) is used for de-noising of ECG signals. The main advantage of SWT de-noising over other de-noising methods such as averaging is that in this method noise is reduced without distortion of the main signal. Also, a signal normalization is performed in the preprocessing step.

Feature extraction is the key point for the final classification performance. Features can be extracted directly from ECG waveform morphology in time or frequency domain. Here a proper combination of timing and sophisticated statistical methods has been considered. Higher order cumulants has been used in order to find features less sensitive to noise.

The main focus of the paper is on the last step of cardiac arrhythmia analysis, i.e., ECG signal classification. A large number of approaches have been proposed for this task, and one of the most popular ones is radial basis function (RBF) neural network. However, finding the optimum value of its parameters is a challenging problem. They were specified tentatively, that is time consuming and not optimum. Here, Bees algorithm (BA) is used to tune these parameters. BA is a recently proposed optimization method that is fast and easy to implement compared to the other optimization algorithms such as genetic algorithms and ant colony.

The rest of paper is organized as follows. Section 2 lists some related works. Section 3 describes the preprocessing part. Section 4 explains the feature extraction. Section 5 presents the classifier and optimization. Section 6 explains the database and performance metrics. Section 7 shows some simulation results. Section 8 discusses the results and finally Section 9 concludes the paper.

2. Related work

In the literature, several methods have been proposed for the automatic classification of ECG signals in Refs. [1–19]. In Ref. [1], the

* Corresponding author. Tel.: +98 1113210982.

E-mail address: abrahamzadeh@gmail.com (A. Ebrahimzadeh).

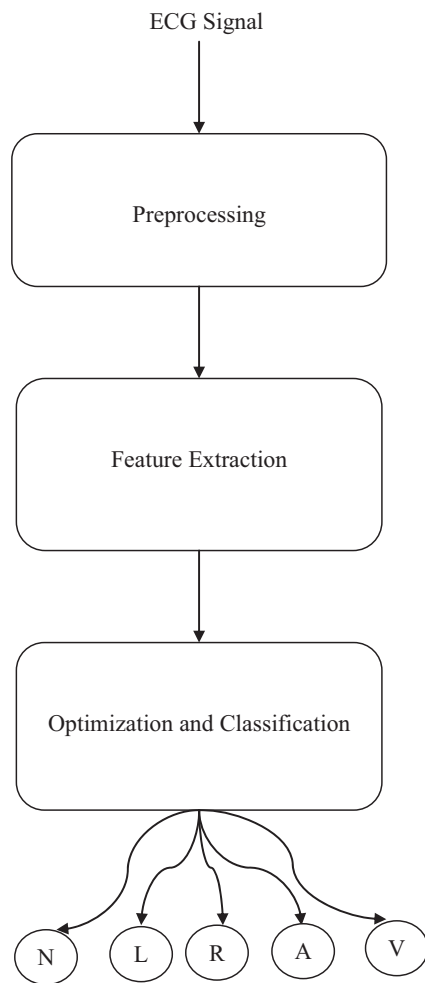


Fig. 1. Block diagram of a typical ECG beat classification system.

authors proposed artificial neural networks (ANN) to classify ECG signal data into two classes. In Ref. [2], the authors presented a new diagnosis system for myocardial infarction classification by converting multilead ECG data into a density model. A hybrid system with hidden Markov models (HMMs) and Gaussian mixtures models (GMMs) employed for data classification. In Ref. [3], the authors introduced a new system for ECG beat classification using support vector machines (SVMs) classifier with rejection. A set of features including frequency information, RR intervals, QRS morphology and AC power of QRS detail coefficients exploited to characterize each beat. In Ref. [4], the authors used combining morphological and statistical features and also investigated a number of different feed forward neural network architectures. In Ref. [5], the authors presented the evaluation of mental stress assessment using heart-rate variability (HRV). In Ref. [6], authors presented a thorough experimental study to show the superiority of the generalization capability of the support vector machine (SVM) approach in the automatic classification of electrocardiogram (ECG) beats and also a novel classification system based on particle swarm optimization (PSO) is proposed to improve the generalization performance of the SVM classifier. In Ref. [7], authors presented an effective cardiac arrhythmia classification algorithm using the heart rate variability (HRV) signal. In Ref. [8], a new clustering method based on kernelized fuzzy *c*-means algorithm and an ant based optimization algorithm, hybrid ant colony optimization for continuous domains, proposed. In Ref. [9], a novel supervised neural network-based algorithm is designed to reliably distinguish in electrocardiographic (ECG) records between normal and ischemic beats of the same

patient. In Ref. [10], the authors proposed a novel independent components (ICs) arrangement strategy to cooperate with the independent component analysis (ICA) method used for ECG beat classification. In Ref. [11], the authors investigated the application of stationary wavelet transform (SWT) for noise reduction of the electrocardiogram (ECG) signals. Feature extraction module extracts 10 ECG morphological features and one timing interval feature. Then a number of multilayer perceptron (MLP) neural networks are used as classifier. In Ref. [12], the authors used proper combination of the morphological and timing interval as features. As the classifier, several supervised classifiers are investigated; they are: a number of multi-layer perceptron neural networks, support vector machines, radial basis function and probabilistic neural networks. In Ref. [13], the authors considered features from the RR series, as well as features computed from the ECG samples and different scales of the wavelet transform, at both available leads. In Ref. [14], the authors have used Heartbeat fiducial point intervals (RR-intervals) and ECG morphology features (samples of QRS complex and T-wave) as features and back propagation as classifier. In Ref. [15], a diverse set of features including higher order statistics, morphological features, Fourier transform coefficients, and higher order statistics of the wavelet package coefficients are extracted for each different type of ECG beat. Optimal features are chosen by using a wrapper type feature selection algorithm. The *k*-nearest neighbor algorithm is employed as the classifiers. In Ref. [16], the authors investigated the use of higher order spectra parameters to identify the most common multiple cardiac arrhythmias. In Ref. [17], the authors represented the application of genetic algorithm for the integration of neural classifiers combined in the ensemble for the accurate recognition of heartbeat types on the basis of ECG registration. In Ref. [18], feature selectors is to developed based on nonlinear correlations in order to select the most effective and least redundant features from an ECG beat classification system based on higher order statistics of sub band components and a feed-forward back-propagation neural network, denoted as HOS-DWT-FFBNN. In Ref. [19], the author used higher order statistics (HOS) of wavelet packet decomposition (WPD) coefficients for the purpose of automatic heartbeat recognition. The obtained feature set is used as input to a classifier, which is based on KNN algorithm.

In this paper, automatic method for classification of cardiac signals is proposed in five different classes. For feature extraction module, a good set of features is used that includes both statistical and temporal features. Then, hybrid Bees algorithm-radial basis function (RBF_BA) neural networks are used as classifier. Finally, some experiments have been prepared to compute their performances and compare them.

3. Signal preprocessing

Denosing is an important issue for the analysis of signals. The most troublesome noise sources are electrical activity of muscles (EMG) and instability of electrode–skin contact [20]. To eliminate such noise, an advanced signal processing technique using discrete wavelet transform (DWT) denoising technique should be used [21]. However, DWT is a decimated wavelet transform. To solve the problem, the stationary wavelet transform (SWT) is used as the undecimated wavelet transforms (UWT). At each level, low-pass and high-pass filter is applied to the input signal in the stationary wavelet transform (SWT) and the discrete wavelet transform (DWT) is similar. In the SWT, the output signal is never subsampled (not decimated). Instead, the filters are upsampled at each level [22].

Suppose the signal $s \in L^2(R)$. The SWT is given by:

$$w_v(\tau) = \frac{1}{\sqrt{v}} \int_{-\infty}^{\infty} s(t) \psi^* \left(\frac{t-\tau}{v} \right) dt \quad (1)$$

Download English Version:

<https://daneshyari.com/en/article/495339>

Download Persian Version:

<https://daneshyari.com/article/495339>

[Daneshyari.com](https://daneshyari.com)