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Arrhythmia Detection and Classification Using Wavelet and ICA

Vahid R. Sabzevari
Azad University of Mashhad, Iran

Asad Azemi
The Pennsylvania State University, USA

Morteza Khademi
Ferdowsi University of Mashhad, Iran

Hossein Gholizade
Ferdowsi University of Mashhad, Iran

Armin Kiani
Ferdowsi University of Mashhad, Iran

Zeinab S. Dastgheib
Ferdowsi University of Mashhad, Iran

INTRODUCTION

The classification of an electrocardiogram (ECG) into different pathophysiological disease categories is a complex pattern recognition task. Computer-based classifications of the ECG can achieve high accuracy and offer the potential of an affordable mass-screening for cardiac abnormalities. Successful classification is achieved by finding the characteristic shapes of the ECG that discriminate effectively between the required diagnostic categories. Conventionally, a typical heart beat is identified from the ECG, and the component waves of the QRS, T, and possibly P waves are characterized using measurements such as magnitude, duration, and area. Datasets that are used for heart diseases involve different features. Some of them are based on laboratory experiments, while others include clinical symptoms. However, one of the most popular and useful databases is the MIT-BIH (http://physionet.fri.uni-lj.si/physiobank/database/mitdb/). Researchers have used this database to test their various algorithms for arrhythmia detection and classification. Two of the most popular methods are artificial neural networks (ANNs) and wavelet transforms, and their variations. For example, Lee (1990) classified three types of cardiac arrhythmias with accuracies of 99.55%, 97.75%, 57.1%, respectively using ANNs. Chi and Jaberi (1992), using triple neural networks, classified ventricular arrhythmia with the average accuracy of 95.1%. Karlik and Ozbey (1996) were able to classify 10 types of arrhythmia with average accuracy of 95%. Hu (1997), using self-organizer neural networks and the Linear Vector Quantization, was able to classify heart beats with average accuracy of 91.3% and 90.3%, respectively. Gholam Hosseini, Rainolds, and Powers (2001) implemented a multistage neural network with two MLPs, and were able to classify five kinds of arrhythmia. At the first stage, they achieved an average accuracy of 81.8%, and at the second stage, 88.3%. The algorithms developed in these works are based on analyzing the ECG signals, which requires a large simulation time.

Selected examples of using wavelet transforms and their variations for arrhythmia classification include the following. Yang, Hu, and Shyu (1997), using dyadic wavelets to extract features, and Kohonen self-organizing neural networks for classification, were able to obtain an average precision of 97.77% for heart disease diagnosis. Dokur, Olmez, and Yazgan (1999) used discrete wavelet transforms to classify ten types of arrhythmias with a precision of 97%. De Chazal, Celler, and Reilly (2000), using a set of 500 records with 345 abnormal cases, classified arrhythmias by using 15 feature sets of three Daubechies wavelets decomposition level and reached the maximum precision of 74.2%. Finally, Dokur and Olmez (2001), using wavelet transforms and ANNs trained by genetic algorithms back propagation, were able to classify 10 types of arrhythmia with a precision of 96%.

The goal of this article is to optimize the feature extraction process by using ICA and wavelet transform, apply the obtained set to several different machine learning schemes, and compare their performances. The article is structured as follows. Section 2.0 describes our proposed method for cardiac arrhythmias detection. Section 3.0 covers an overview of different classifier types that were used in this work. Sections 4.0 and 5.0 summarize our simulation scheme and results. Finally, section 6.0 presents the concluding remarks.

PROPOSED METHOD

Figure 1 presents the block diagram of the proposed detection and classification process. First, the appropriate components of the ECG signal are obtained by using the ICA algorithm. Next, these components are used to calculate the coefficients of the Daubechies wavelets. Based on this step, proper features are selected and fed into the classifier. For comparison purposes, three different machine learning methods have been implemented—namely, radial basic function (RBF), multilayer perceptrons (MLPs), and K-nearest neighbor (KNN).

Next, we will present an overview of the ICA and wavelet transform.

Independent Component Analysis with a Time Structure Method

To rigorously define ICA, we can use a statistical "latent variables" model. We observe n random variables $x_1,\dots,x_n$, which are modeled as linear combination of n random variables $s_1,\dots,s_n$:

$$x_i = a_{i1}S_1 + a_{i2}S_2 + \dots + a_{in}S_n \quad i = 1,\dots,n \qquad (1)$$

Where a_{ij}, $i,j=1, \dots, n$ are some real coefficients. By definition, the s_i are statistically and mutually independent.

This is the basic ICA model. The ICA model is a generative model, which means that it describes how the observed data are generated by a process of mixing the components s_i. The independent components s_i (often abbreviated as ICs) are latent variables, meaning that they cannot be directly observed. Also, the mixing coefficients a_{ij} are assumed to be unknown. All we observe are the random variables x_i, and we must estimate both the mixing coefficients a_{ij} and the ICs s_i using the x_i.

Here, we have dropped the time index t, because in this basic ICA model, we assume that each mixture x_i, as well as each independent component s_i, is a random variable, instead of a proper time signal or time series.

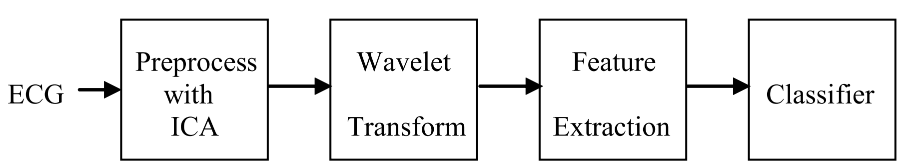
If the independent components (ICs) are time signals, the situation is quite different. In many applications, however, what is mixed is not random variables, but time signals, or time series. This is in contrast to the basic ICA model in which the samples of x have no particular order; we could shuffle them in any way we like, and this would have no effect on the validity of the model. In fact, if the ICs are time signals, they may contain much more structure than simple random variables.

In this research, we consider the estimation of the ICA model when the ICs are time signals, $s_i(t), t=1,\dots,T$, where t is the time index. Here, t has a more precise meaning, since it defines an order between the ICs. The model is then expressed by:

$$x(t) = As(t) \qquad (2)$$

where A is assumed to be square as usual and the ICs are of course independent. We shall make some as-

Figure1. Block diagram of the proposed detection-classification system



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