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Technical Note

A multi-wavelet optimization approach using similarity measures for electrocardiogram signal classification

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ABSTRACT

One of the main approaches for classifying the ECG signals is the use of wavelet transform. In this paper, a method has been presented for classifying the ECG signals by means of new wavelet functions (WFs). The considered approach for generating the new WFs relies on the degree of similarity between the shapes of the WFs and ECG signals. Thus, by formulating the wavelet design problem in the hybrid GA-PSO framework, and using Euclidean, Dynamic Time Warping, Signed Correlation Index, and Adaptive Signed Correlation Index similarity measures as wavelet design criterion, six WFs corresponding to six common arrhythmias have been designed. Decomposition of ECG signal using designed WFs, and thereafter, application of PCA, and multilayer perceptron classifier provides a classification scheme for ECG signals. Feature vector is obtained by applying all designed WFs to every single beat; so, the main advantage of this method is that the set of WFs used to decompose the beats, always includes a WF similar to those beats. Therefore, the generated features better resolve the various classes. Also, the effects of the number of neurons in the hidden layer and the different training methods of the MLP have been investigated. By performing some tests on the benchmark MIT-BIH arrhythmia database using the proposed method and also the common WFs, the superiority of the proposed approach in the overall accuracy as well as the accuracy of each class has been demonstrated.

1. Introduction

An electrocardiogram characterizes the electrical activities of a heart, which are recorded through several electrodes attached to the skin. This quasi-periodic signal contains valuable information on the functioning of a heart and can be used for the detection of heart disease [1]. The automatic detection of arrhythmia, including the detection of abnormal P, QRS and T waves and distinguishing them from normal heart rhythms could be very useful for an early detection of heart disease, especially in real time. One of the complexities of the ECG analysis is the enormous variety of waveforms that exist not only in different arrhythmias, but also within different time intervals for a particular arrhythmia.

Using wavelet transform enables us to analyze a signal in different frequency bands. For this reason, the wavelet transform technique is extensively used today in the de-noising, compression and classification of biological signals, especially the ECG signals [2].

There are a number of new approaches for the classification of ECG signals. Martis et al. [3] used DWT coefficients and dimension reduction methods to feed SVM, PNN and NN in order to classify five arrhythmias. Using the morphological features and the RR intervals, as the feature vectors, and the mixture of experts (ME) and negatively correlated learning (NCL), Javadi et al. [4] classified ECG signals into normal and abnormal classes. Yu and Chen [5] classified six types of arrhythmias by considering three statistical features of the wavelet coefficients in addition to the RR interval and by employing the PNN. Khazaee and Ebrahimzadeh [6] classified five types of ECG beats by proposing a power spectral-based hybrid Genetic Algorithm and Support Vector Machine (SVMGA) technique. Using 64 features including 48 statistical features of wavelet coefficients and 16 morphological features, Rai et al. [7] classified a number of ECG signals into normal and abnormal ones by applying the MLP, FFN and BPN classifiers.

On the other hand, there are some methods using optimization methods to classify ECG beats. Dogan and Korurek [8] classified six types of ECG beats using Ant Colony Optimization for Continuous Domains and a radial basis function neural network. Dilmac and Korurek [9] proposed a new Modified Artificial Bee Colony (MABC)

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algorithm for data clustering and applied it to ECG signal analysis for classification.

It is noticeable that in all the mentioned works, a common wavelet function (WF) has been used. Nevertheless, Senhaji et al. [10] showed that no WF can be considered the most appropriate to use in classifications and that the ultimate decision must be made by comparing the results of different wavelets for each specific case.

So, some research works have been carried out to find the most appropriate WF for the classification and denoising of ECG signals. For example, Daamouche et al. [11] presented an innovative approach for generating appropriate WFs used in the classification of ECG signals. In this approach, a polyphase representation of wavelet filter banks has been used and the considered problem has been formulated in the particle swarm optimization (PSO) framework. The results show that the proposed wavelet is superior to the Daubechies and Symlet wavelet families. Tan et al. [12] proposed the Best WF Identification System to identify and select the WF which is better suited to denoising a given ECG signal. Kumari et al. [13] designed two new wavelets by using the polyphase representation of wavelet filter banks and considering the perfect reconstruction conditions as the cost function.

As was pointed out, the main approach of all the previous works on the design of WFs is the use of one WF for the classification of all types of beats. In this paper, six different WFs have been used to classify six common arrhythmias. For this purpose, first, by introducing a WF design by means of polyphase representation, an optimization problem is formulated for finding the right angular parameters. By solving this optimization problem for each arrhythmia, the angular parameters that generate the low-pass and high-pass filter coefficients of a WF correspond to that arrhythmia are found. Due to the complexity of the optimization problem, the hybrid GA-PSO approach has been used in order to benefit from the positive characteristics of both the genetic algorithm and the particle swarm optimization approaches. The cost function used in the optimization algorithm expresses the degree of resemblance of the generated WF to the shape of an arrhythmia. To assess the degree of similarity between a WF and the shape of an arrhythmia, Euclidean, Dynamic Time Warping, Signed Correlation Index, and Adaptive Signed Correlation Index similarity measures have been employed. Then by decomposing the ECG signal using these six WFs and by applying the PCA method separately on the approximation and detail coefficients at level 4 and putting together the obtained results, the feature vector used in the classification process have been developed. Then, the MLP classifier has been used to classify the ECG signals. At the end, the performance of the proposed algorithm on MIT-BIH database has been investigated.

The remainder of this paper has been organized as follows. Section 2 gives a general review of wavelets, optimization approaches, feature extraction method, and the MLP classifier. Section 3 describes the proposed method. Section 4 deals with database description and performance indices. Results and discussion are provided in Section 5. And finally, the paper concludes in Section 6.

2. Materials and methods

2.1. Discrete wavelet transform

In multiresolution framework, a signal is represented at different scales, each having a different resolution. Each scale spans the entire time/spatial range of the input signal, but does not represent the original signal completely [14]. The discrete wavelet transform (DWT) is related to multirate filter banks. It is performed by applying low-pass and high-pass filters on the input signal and then downsampling the signal by two [15]. First, let us introduce the scaling and WFs,

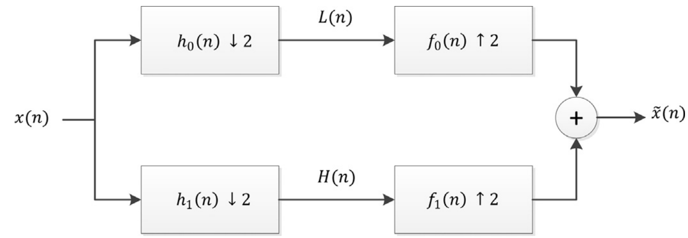

Fig. 1. A block diagram of a two-channel filter bank.

$$\phi(t) = \sum_n h_0(n)\phi(2t-n) \tag{1}$$

$$\psi(t) = \sum_n h_1(n)\phi(2t-n) \tag{2}$$

Eqs. (1) and (2) are called the dilation and wavelet equations, and $\phi(t)$ and $\psi(t)$ are called the scaling (corresponding to a low-pass filter) and wavelet (corresponding to a high-pass filter) functions, respectively [16]. The left-hand sides of (1) and (2) are expressed through the sets of functions of the form $\{\phi(2^j t-n)\}$, where parameters j and n are the dilation and translation parameters.

Fig. 1 shows the DWT process for signal $x(n)$. Signal $x(n)$ gets downsampled by two and filtered through filters $h_0(n)$ and $h_1(n)$. These two filters are called "analysis filters" [14]. After being processed, the signal is filtered by $f_0(n)$ and $f_1(n)$, which are called "synthesis filters". The signals from the two channels are upsampled and combined to produce an output signal at the original rate [14]. A filter bank consisting of the filters that allow the original signal to be recovered without any distortion is called a perfect reconstruction (PR) filter bank [15].Let the analysis low-pass filter in a two-channel PR orthonormal filter bank has $2N$ coefficients as $\{h_0(i)\}$

Then, in the z domain we have,

$$\begin{aligned} H_0(z) &= \sum_{i=0}^{2N-1} h_0(i)z^{-i} = \sum_{i=0}^{N-1} h_0(2i)z^{-2i} + z^{-1}\sum_{i=0}^{N-1} h_0(2i+1)z^{-2i} \\ H_{00}(z) &= \sum_{i=0}^{N-1} h_0(2i)z^{-2i} \\ H_{01}(z) &= \sum_{i=0}^{N-1} h_0(2i+1)z^{-2i} \end{aligned} \tag{3}$$

where $H_{00}(z)$ and $H_{01}(z)$ are the polyphase components (even and odd powers of z [17,18]) of $H_0(z)$. The following factorization of the polyphase matrix was proposed in [17],

$$H_p(z) = \begin{pmatrix} H_{00}(z) & H_{01}(z) \\ H_{10}(z) & H_{11}(z) \end{pmatrix} = \begin{pmatrix} c_0 & s_0 \\ -s_0 & c_0 \end{pmatrix} \cdot \prod_{i=1}^{N-1} \begin{pmatrix} 1 & 0 \\ 0 & z^{-1} \end{pmatrix} \cdot \begin{pmatrix} c_i & s_i \\ -s_i & c_i \end{pmatrix} \tag{4}$$

where $H_{10}(z)$ and $H_{11}(z)$ are the polyphase components of the high-pass analysis filter $H_1(z)$, and $c_i = \cos(\alpha_i)$ and $s_i = \sin(\alpha_i)$.

This factorization generates all the two-channel PR orthonormal filter banks with an impulse response length of $2N$, i.e., any such filter bank can be written in terms of N parameters (α_i) by taking the values from interval $[0, 2\pi)$. A new formulation was proposed in [19] by rewriting the above factorization in the following general recursive form,

$$H_p^{(k+1)}(z) = H_p^{(k)}(z) \cdot \begin{pmatrix} 1 & 0 \\ 0 & z^{-1} \end{pmatrix} \cdot \begin{pmatrix} c_k & s_k \\ -s_k & c_k \end{pmatrix} \quad k = 1, 2, \ldots, N \tag{5}$$