Biomedical Signal Processing and Control 7 (2012) 342–349

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

A wavelet optimization approach for ECG signal classification

Abdelhamid Daamouche [a], Latifa Hamami [b], Naif Alajlan [c], Farid Melgani [a,*]

[a] Department of Information and Communication Technologies, University of Trento, Trento, Italy
[b] School of Engineering, El Harrach, Algiers, Algeria
[c] ALISR Laboratory, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

ARTICLE INFO

Article history:
Received 5 May 2011
Received in revised form 14 June 2011
Accepted 4 July 2011
Available online 30 July 2011

Keywords:
Classification
Discrete wavelet transform (DWT)
Electrocardiogram (ECG) signals
Particle swarm optimization (PSO)
Support vector machines (SVM)

ABSTRACT

Wavelets have proved particularly effective for extracting discriminative features in ECG signal classification. In this paper, we show that wavelet performances in terms of classification accuracy can be pushed further by customizing them for the considered classification task. A novel approach for generating the wavelet that best represents the ECG beats in terms of discrimination capability is proposed. It makes use of the polyphase representation of the wavelet filter bank and formulates the design problem within a particle swarm optimization (PSO) framework. Experimental results conducted on the benchmark MIT/BIH arrhythmia database with the state-of-the-art support vector machine (SVM) classifier confirm the superiority in terms of classification accuracy and stability of the proposed method over standard wavelets (i.e., Daubechies and Symlet wavelets).

1. Introduction

The electrocardiogram (ECG) signal represents the changes in electrical potential during the cardiac cycle as recorded between surface electrodes on the body [1]. The analysis of ECG signals can provide clinicians with valuable information about the patient health condition. In this context, significant research efforts have been devoted for developing automatic and fast arrhythmia diagnosis tools based on the processing and analysis of ECG signals.

In the last two decades, wavelets have attracted a growing interest in many signal processing and analysis applications. The main interesting feature of wavelets is their time-frequency representation of the signal. They allow gaining a deep insight of the signal at different scales and frequencies, and have proved particularly successful both in ECG signal compression and classification [1–13].

In the context of ECG signal classification which represents the focus of this paper, several interesting works can be found in the literature. In particular, in [4], Ince et al. proposed a feature extraction technique that employs the translation-invariant dyadic wavelet transform in order to effectively extract the morphological information from ECG data. In [5], Sahambi et al. presented an approach that uses a dyadic wavelet to characterize the ECG signal. To circumvent its high computational cost, they used digital signal processing add-on cards. In [6], a method for detecting premature ventricular contraction (PVC) from the Holter system is proposed using wavelet transform and fuzzy neural network. In [7], Dickhaus et al. addressed two questions: how are the recorded time courses of the signals to be interpreted with regard to a diagnostic decision? What are the essential features and how is the information hidden in the signals? Then they presented an example to identify patients who are at high-risk of developing ventricular tachycardia (VT). In [8], an approach to detect PVCs using a neural network with weighted fuzzy membership functions is described. To discriminate between normal and PVC beats, Lim et al. exploited wavelet coefficients. In [9], a dyadic wavelet transform is used for extracting ECG characteristic points. The local maxima of the wavelet modulus at different scales are used to locate the sharp variation points of ECG. The proposed algorithm first detects the QRS complex, then the *T* wave, and finally the *P* wave. In [10], Khamene and Negahdaripour proposed a solution that relies on the positions of singular points (high peaks) of the ECG signal. Their method attempts to discriminate between the singular points of the maternal and fetal ECGs, both present in the composite abdominal signal. All the work is carried out in the wavelet transformed space of the ECG signal. In [11], Inan et al. presented an approach for classifying beats of a large dataset by training a neural network classifier using wavelet and timing features. They found that the fourth scale of a dyadic wavelet transform with a quadratic spline wavelet together with

* Corresponding author.
E-mail address: melgani@disi.unitn.it (F. Melgani).

1746-8094/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.bspc.2011.07.001

the pre/post RR-interval ratio is very effective in distinguishing normal and PVC from other beats. In [12], features extracted from successive wavelet coefficient levels after wavelet decomposition of signals of heart rate variability (HRV) from RR intervals and ECG-derived respiration (EDR) from R waves of QRS amplitudes were used as inputs to a support vector machine (SVM) classifier to recognize obstructive sleep apnea syndrome. In [13], Senhaji et al. raised an important question: what is the most appropriate wavelet to use? The answer was: there is no theoretical answer at the moment and the choice must be done empirically by comparing results of different wavelets.

All the aforementioned works made use of wavelets which have been derived for general signal processing and analysis. However, we believe that in order to improve wavelet performances in ECG classification, one should design wavelets that are optimized for this specific problem. This paper is intended to propose a wavelet design method which is driven by the classification process performance in terms of accuracy. Due to the very complex relationship characterizing the wavelet and the classifier accuracy, we resort to a stochastic design method based on particle swarm optimization (PSO) which has proved capable to provide effective answers to problems raised by various applications [14–16]. The proposed method exploits the polyphase representation of the discrete wavelet transform (DWT). Such representation allows generating a wavelet filter bank from a set of angular parameters, and thus formulating the wavelet design problem for ECG signal classification as a problem of estimating these parameters so that to maximize the classifier accuracy. The kind of classification approach adopted in this work is the state-of-the-art SVM classifier known for its high generalization capability.

The remaining of this paper is organized as follows. Section 2 gives a general review of wavelets. Sections 3 and 4 present the main principles of PSO and SVM, respectively. Section 5 describes the proposed wavelet design method. Experimental results are provided in Section 6. Finally, conclusions are drawn in Section 7.

2. Wavelets

The wavelet transform is a linear operation that decomposes a signal into components that appear at different scales [1,5,17]. Wavelet functions $\Psi(t)$ are defined in a space of measurable functions that are absolute and square integrable, i.e.,

$$\int_{-\infty}^{+\infty} \left|\Psi(t)\right| dt < \infty \tag{1}$$

$$\int_{-\infty}^{+\infty} \left|\Psi(t)\right|^2 dt < \infty \tag{2}$$

In such a space, they should satisfy conditions of zero mean and square norm one [17]:

$$\int_{-\infty}^{+\infty} \Psi(t)dt = 0 \tag{3}$$

$$\int_{-\infty}^{+\infty} \left|\Psi(t)\right|^2 dt = 1 \tag{4}$$

The wavelet transform of a function $f(t) \in L^2(R)$ at scale a and position τ is given by [5]:

$$Wf(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\Psi^* \left(\frac{t-\tau}{a}\right) dt \tag{5}$$

The asterisk * denotes the complex conjugation.

Eq. (5) means that the signal to be analyzed $f(t)$ is convolved with stretched/dilated copies of the mother wavelet $\Psi(t)$. For $a < 1$, the wavelet is contracted and the transform gives information about the finer details of $f(t)$. For $a > 1$, the wavelet expands and the transform gives a coarse view of the signal. If the scale parameter $a = 2^j$ with $j \in Z$, Z is an integer set, then the wavelet is called a dyadic wavelet [17]. The wavelet transform operates in continuous time on functions and in discrete time on vectors. In continuous time, the wavelet coefficients are found by evaluating the integral in (5). Whereas, in discrete time, the coefficients are found by passing a vector ($x(n)$, n integer) through a bank of two filters, one is a low-pass and the other is a high-pass.

A complete and interesting characterization of the DWT filter coefficients with compact support was presented by Daubechies in [18]. However, in general, since looking for an optimum wavelet is a problem-dependent issue, DWT design can take many forms. In this context, an elegant way to determine the coefficients of a filter bank has been developed by Sherlock and Monro [19]. It is a polyphase method [20] which relies on a factorization proposed by Vaidyanathan [21]. Their algorithm allows deriving any orthonormal perfect-reconstruction finite impulse response (FIR) filter of arbitrary length. In the following, the method is briefly described. The low-pass filter coefficients in the z-domain are given by:

$$H_0(z) = \sum_{i=0}^{2N-1} h_i z^{-i} \tag{6}$$

and thus

$$H_0(z) = \sum_{i=0}^{N-1} h_{2i} z^{-2i} + z^{-1} \sum_{i=0}^{N-1} h_{2i+1} z^{-2i} \tag{7}$$

In (7), H_0 is decomposed into even and odd powers of z. Vaidyanathan proposed the following factorization of the polyphase matrix [21]:

$$H_p(z) = \begin{pmatrix} H_{00}(z) & H_{01}(z) \\ H_{10}(z) & H_{11}(z) \end{pmatrix} = \begin{pmatrix} c_0 & s_0 \\ -s_0 & c_0 \end{pmatrix} \prod_{i=1}^{N-1} \begin{pmatrix} 1 & 0 \\ 0 & z^{-1} \end{pmatrix} \begin{pmatrix} c_i & s_i \\ -s_i & c_i \end{pmatrix} \tag{8}$$

where

$$H_{00}(z) = \sum_{i=0}^{N-1} h_{2i} z^{-2i} \tag{9}$$

and

$$H_{01}(z) = \sum_{i=0}^{N-1} h_{2i+1} z^{-2i} \tag{10}$$

$H_{00}(z)$ and $H_{01}(z)$ represent the polyphase components of the low-pass filter, whereas $H_{10}(z)$ and $H_{11}(z)$ are those of the high-pass filter. The coefficients c_i and s_i are computed as follows: $c_i = \cos(\theta_i)$ and $s_i = \sin(\theta_i)$.

Sherlock and Monro developed a new formulation by rewriting the factorization in a recursive form [19]:

$$H_p^{(k+1)}(z) = H_p^{(k)}(z) \begin{pmatrix} 1 & 0 \\ 0 & z^{-1} \end{pmatrix} \begin{pmatrix} c_k & s_k \\ -s_k & c_k \end{pmatrix} \tag{11}$$