ECG Signals Classification using Statistical and Time-Frequency Features

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Abstract
Cardiovascular diseases are one of the most frequent and dangerous problems in modern society nowadays. Therefore, it is very difficult to take immediate measures without real time electrocardiogram information. Unfortunately ECG signals, during their acquisition process, are affected by various types of noise and artifacts due to the movement, or breathing of the patient, electrode contact, power-line interferences, etc. The aim of this study was to develop an algorithm to detect and classify four types of electrocardiograms (ECG): without noise, or containing one of the following three types of noise: baseline wonder, muscular noise or electrode motion artifact. The classification was made using descriptive statistics. The Stationary Wavelet Transform (SWT) was applied in order to extract features from input signals. The main reasons for using this transform are the properties of good representation of non-stationary signals such as ECG signals and the possibility of dividing the signal into different bands of frequency. The proposed method was tested using real ECG signals affected by noise from the MIT-BIH arrhythmia database. The goal was to analyze the percentage of the well classified signals. The proposed algorithm showed good results, assuring a good classification with more than 90% well classified signals for each type of ECGs.

Keywords: ECG; Wavelet analysis; Noise; Classification.

Introduction

The electrocardiogram (ECG) plays an important role in the process of monitoring and diagnosing cardiac arrhythmias (irregularities in heart rate). Any change in ECG characteristics and interval durations may reflect an abnormality in cardiac conduction. Generally, computer-aided ECG diagnosis includes features recognition and classification processes. An accurate ECG signal, unaffected by low-frequency and high-frequency interferences, is rarely found in practice. The most common disturbing perturbations are: baseline wonder, muscular noise (EMG) or electrode motion artifact. The iso-electric line, measured as the portion of the tracing following the T wave and preceding the next P wave is called baseline. The muscular noise is induced by the patient's movement and it has a large frequency band. Electrode motion artifact is generally considered the most troublesome noise, since it can mimic the appearance of abnormal beats. All these unwanted phenomena make difficult the interpretation of the ECG signal and sometimes even impossible [1].

Biomedical signals such as ECG signals are non-stationary, meaning that they change their statistical properties over time. To analyze this kind of signals the wavelet transform represents a powerful tool. During the last years, the wavelet transform has proved to be a valuable tool for analyzing data from various domains such as mathematics, science, engineering, economics and also

medicine and biology. Results of studies in the literature have demonstrated that the wavelet transform is the most promising method to extract features that characterize the behavior of ECG signals [2-4], or for removing noises [5], or compression [6].

The goals of this paper are to propose a new wavelet based detection and classification algorithm for ECG signals perturbed by different types of noises and to compare the algorithm with an already published one.

Materials and Methods

The Wavelet Transform

The proposed method belongs to the class of time-frequency methods which uses the wavelet transform. The transform of a signal is another form to represent it. It does not affect the information carried by the signal. In this context, a wave is an oscillating periodic function of time or space. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals. While Fourier transform uses waves to analyze signals, the wavelet transform (WT) uses wavelets of finite energy.

The wavelet theory deals with the properties of wavelets. It is a relatively new mathematical tool which appeared around 1980 when Grossman and Morlet [7] broadly defined wavelets in the context of quantum physics. Based on physical intuition, these two researchers provided a new way of thinking for wavelets based on physical intuition. In 1985, S. Mallat [8] gave wavelets an additional jump-start through his work in digital signal processing. He discovered some relationships between quadrature mirror filters, pyramid algorithms, and orthonormal wavelet bases. A couple of years later, in 1988, I. Daubechies [9] used Mallat's work to construct a set of wavelet orthonormal basis functions that are perhaps the most elegant, and have become the cornerstone of wavelet applications today.

The Continuous Wavelet Transform (CWT) [7] is based on a set of analyzing wavelets allowing the decomposition of signals in a set of coefficients. The decomposition is made in terms of both time and frequency (scale), permitting to effectively diagnose the main frequency component and to extract abstract local information from a time series. The main disadvantage of the CWT is that it is computed for a large number of values both for the scale and for the translation, so it is a very redundant transform. Therefore, a discretization of the scale and translation variables was introduced. The Discrete Wavelet Transform (DWT) is obtained by the discretization of the CWT in the time-frequency plane [10] and is used to decompose discrete time signals into a series of successively lower resolution approximation signals and their associated detail signals. At each resolution level, the approximation and the detail signals are needed for the reconstruction of the approximation signal from the previous resolution level. The DWT has two features: the wavelet mother (ψ) and the number of decomposition levels. Discrete wavelets can be scaled and translated in discrete steps and a wavelet representation is the following:

$$\psi(j,n) = \frac{1}{\sqrt{2^j}} \psi(\frac{t - n2^j}{2^j})$$

(1)

where *j* is the scale factor and *n* is the translation index.

Classical DWT is not shift invariant meaning that DWT of a translated version of a signal is not the same as translation of the DWT of the original signal. In order to achieve shift-invariance, the Stationary Wavelet Transform (SWT) has been inntroduced. The SWT is a time-redundant version of the standard DWT. Unlike the DWT, which down-samples the approximation coefficients and detail coefficients at each decomposition level, in the case of SWT no down-sampling is performed. This means that the approximation coefficients and detail coefficients at each level have the same length as the original signal. This determines an increased number of coefficients at each scale and more accurate localization of signal features. Instead the filters are up-sampled at each level. The SWT has the translation-invariance, or shift-invariance, property. Thus, the SWT gives larger

amount of information about the transformed signal compared to the DWT. Larger amount of information is especially important when statistical approaches are used for analyzing the wavelet coefficients. The shift-invariance property is important in feature extraction applications, denoising and detection [11].

The multiresolution analysis (MRA) is a signal processing technique that takes into account the signal's representation at multiple time resolutions [8]. The level of decomposition depends on the length of the data set (the number of values). At each temporal resolution two categories of coefficients are obtained: approximation coefficients and detail coefficients. Generally, the MRA are implemented based on the algorithm of Mallat [8], which corresponds to the computation of the DWT, represented in Figure 1.
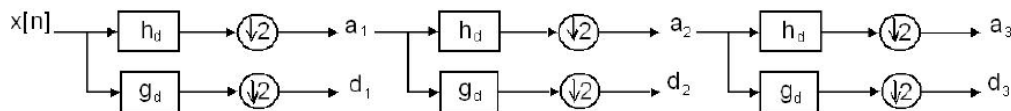

Figure 1. A three order Mallat decomposition tree.

The signal x[n] is passed through a series of high pass filters with the impulse response g_d to analyze the high frequencies and it is passed through a series of low pass filters with the impulse response h_d to analyze the low frequencies. At each level, the high-pass filter produces the detail information d_k, while the low-pass filter associated with scaling function produces coarse approximations, a_k (k = 1, 2, 3). The filtering operations determine the signal's resolution, meaning the quantity of detail information in the signal, while the scale is determined by up-sampling and sub-sampling operations.

Another way to implement a MRA is the use of the algorithm "à trous" proposed by Shensa [12] which corresponds to the computation of the SWT. A three order decomposition tree is represented in Figure 2.
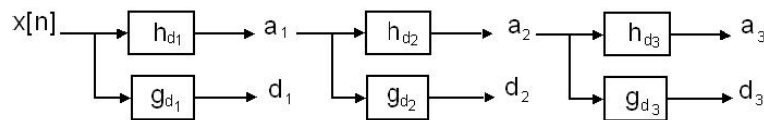

Figure 2. A three order system for the computation of a SWT.

In the case of the SWT the use of decimators is avoided but at each iteration low-pass (h_{d_1}, h_{d_2} and h_{d_3}) and high-pass filters (g_{d_1}, g_{d_2} and g_{d_3}) are used. The difference between SWT and DWT is that the signal is never down-sampled, while the filters are up-sampled at each level in the case of SWT. The SWT offers a more flexible analysis tool than the DWT.

There are several types of wavelet families whose qualities vary according to several criteria such as: the support of the mother wavelets, the symmetry, the number of vanishing moments, the regularity. These are associated with two properties that allow fast algorithm and space-saving coding: the existence of a scaling function and the orthogonality or the biorthogonality of the resulting analysis. A possible classification of wavelets is into two classes: orthogonal and biorthogonal [8]. Based on the application, either of them can be used. There is a variety of mother wavelets such as Daubechies, Symmlet, or Coiflet, which generate orthogonal wavelet bases [8]. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting WT. Therefore, the details of the particular application should be taken into account and the appropriate mother wavelet should be chosen in order to use the WT effectively. The Daubechies (db) wavelets have been increasingly adopted by signal processing researchers. They represent a collection of orthogonal

mother wavelets with compact support, characterized by a maximal number of vanishing moments for some given length of the support. The elements of the Daubechies' family mostly used in practice are db2 - db20. The index refers to the number of vanishing moments. The number of vanishing moments is equal to half of the length of the digital filters in Figure 1 and Figure 2. From the Daubechies wavelets family the most similar in shape to a real ECG signal is db6 showed in Figure 3. For this reason db6 mother wavelets was used in the proposed algorithm.
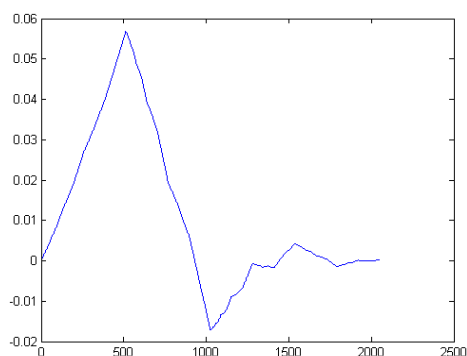
Figure 3. The mother wavelets db6.

Database

The classification algorithm proposed in this paper is tested using an ECG signal (the'108' recording) from MIT-BIH Arrhythmia Database and the three types of noise from MIT-BIH Noise Stress Test (NST) Database [15]. The NST database includes 12 half-hour ECG recordings and 3 half-hour recordings of noise typical in ambulatory ECG recordings. The noise recordings were made using physically active volunteers and standard ECG recorders, leads and electrodes. The three noise records were assembled from the recordings by selecting intervals that contained predominantly baseline wander (in record 'bw'), muscle (EMG) artifact (in record 'ma'), and electrode motion artifact (in record 'em'). The four types of signals that will be used in the simulations part are represented in the following figures: ECG without noise (Figure 4 a), ECG affected by baseline wander (Figure 4 b), ECG affected by electrode motion artifact (Figure 4 c) and ECG affected by muscular noise (Figure 4 d). The length of each signal is 4096.

a

b

c

d
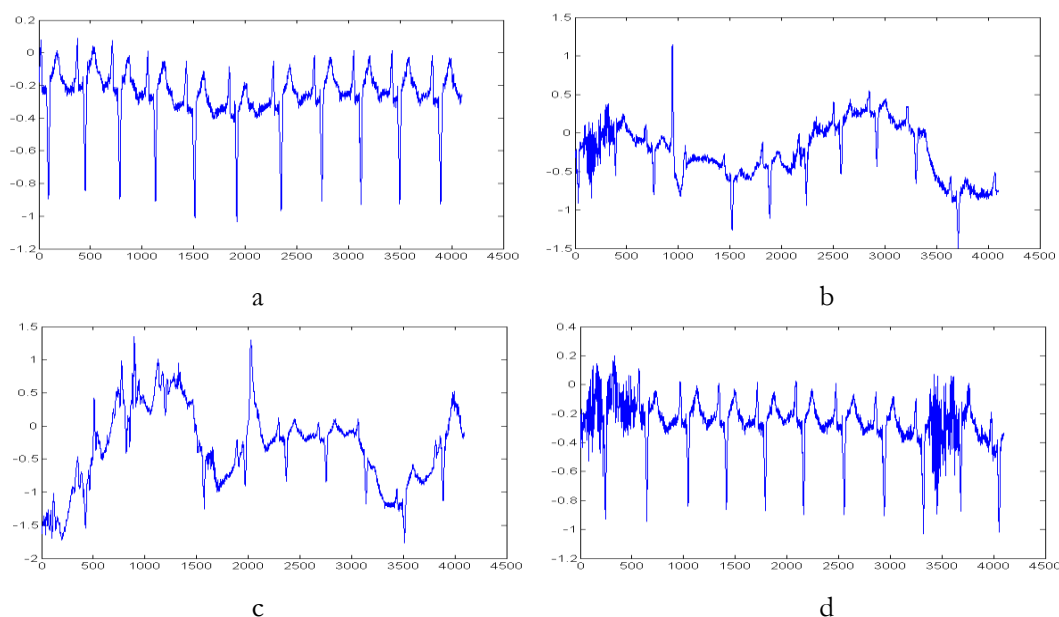
Figure 4. (a) ECG signal without noise; **(b)** ECG signal+baseline wonder (bw); **(c)** ECG signal+electrode motion artifact (em); **(d)** ECG signal+muscular noise (ma).

Algorithm

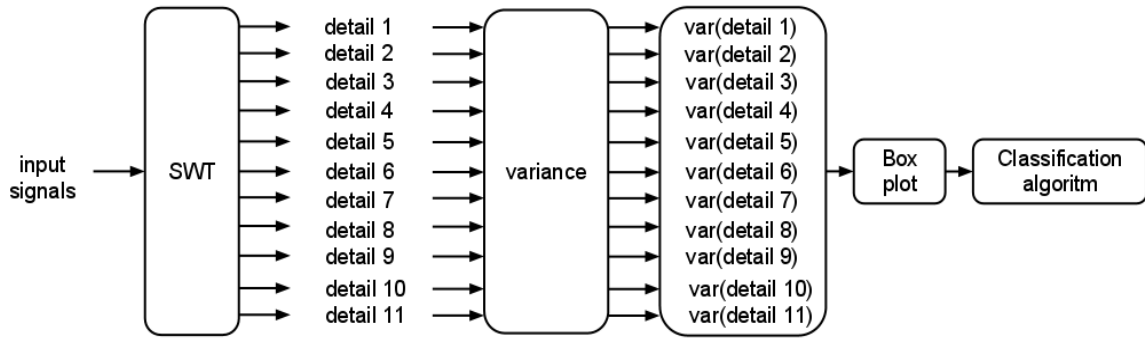The proposed algorithm is shown in Figure 5.

Figure 5. The proposed algorithm.

The input signals were decomposed into eleven levels and we choose only the detail coefficients. We considered one hundred signals of each type. The classification procedure implies the use of the box plot, also called "box-and-whiskers plot", a quick graphic approach which is useful for summarizing data [13]. A detailed description of box plots is given in [14]. To apply the box plot function on the data set, the variance of the data set was calculated. The box plot function was applied for each level of decomposition and eleven diagrams as the ones presented in Figure 6 were obtained.
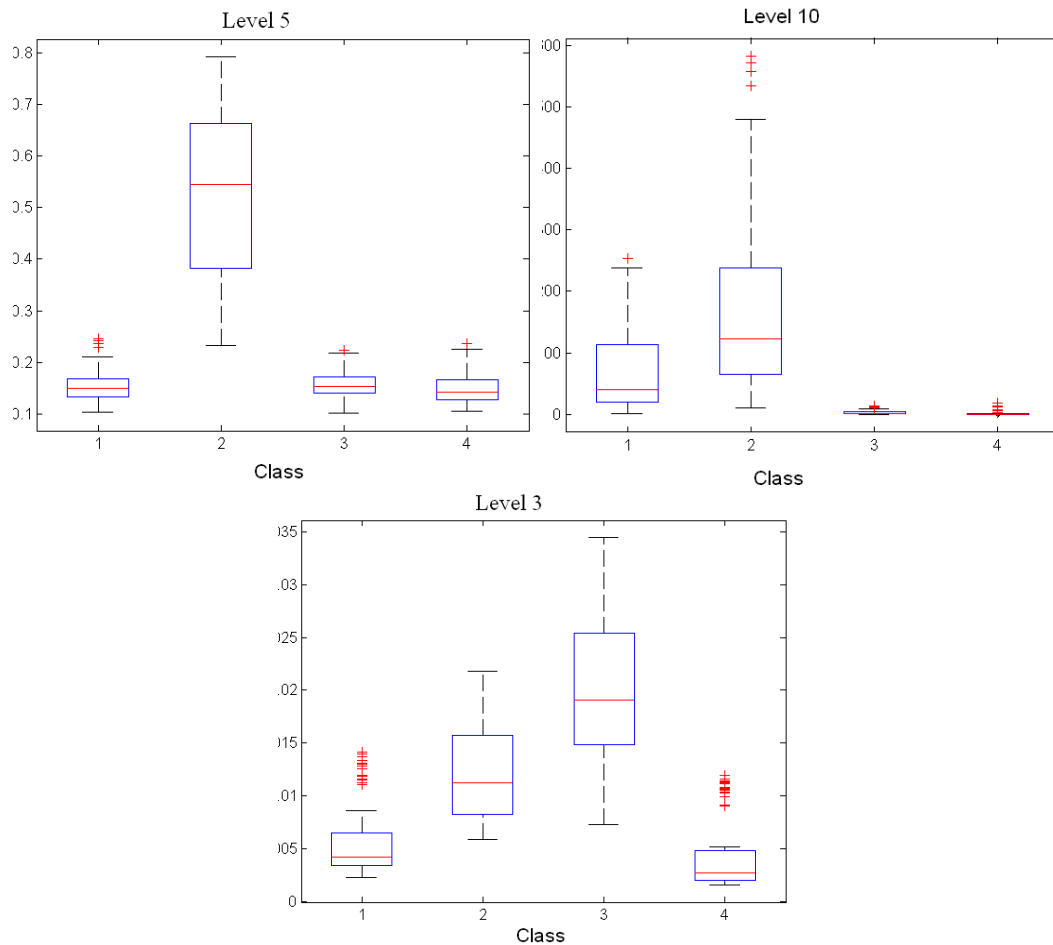

Figure 6. Box plot function applied to various levels of decomposition

The four classes showed in Figure 6 correspond to the four types of signals used for simulations: class 1 - ECG+bw, class 2 - ECG+em, class 3 - ECG +ma, class 4 - ECG. The algorithm consist in finding 'a limit' to differentiate the four types of signals (classes) related to this limit. The best separation was obtained selecting the detail coefficients from the fifth decomposition level, from the third decomposition level and from the tenth decomposition level respectively. It can be observed, analyzing Figure 6 a) that the second type of signals is very well separated of the other three types of signals at the 5'th decomposition level. The fifth and the tenth decomposition levels were used to delimit the other three signals. Next, the detection and classification are performed.

Results and Discussion

The tests were made using Matlab software and WaveLab 850 toolbox. The classification results are showed in Table 1.

Table 1. Classification of the four types of signals

Signals	Classification percentage (%)
ECG+bw	93
ECG+em	100
ECG+ma	98
ECG	80

We can observe that proposed algorithm gives very good classification percentages: 93% for ECGs perturbed by baseline wandering, 98% for ECGs corrupted by muscular noise and even 100% for ECG+em signals.

In [16] was developed an algorithm of detection and classification using the DWT and statistical features. In this paper the DWT was replaced with the SWT and the algorithm was tested using the same ECG signals as in [16] in order to compare the two algorithms. For both methods one hundred signals of each of the four types of ECGs showed in Figure 4 were used. The classification results are showed in Table 2.

Table 2. Comparison between classification percentages using the DWT based algorithm and SWT based algorithm.

Signals	Classification percentage	
	DWT (%)	SWT (%)
ECG+bw	91	93
ECG+em	96	100
ECG+ma	94	98
ECG	74	80

Compared to the algorithm proposed in [16], the method in which the input signals are decomposed using the SWT show higher classification percentage for all the four types of signals. For the second type of ECGs, perturbed by electrode motion artifact, the classification percentage is 100% to the 96% in the case of DWT based decomposition algorithm. Also, for the third type of ECGs (perturbed by muscular noise), the signals are very well classified (98% well classified signals). For the forth type of ECGs we obtain only 74% well classified signals in the case of using DWT and 80% in the case of using SWT. The explanation is very simple: the record '108' taken from MIT-BIH Arrhythmia Database to denote a 'clean' ECG was considered 'clean' meaning that it was not intentionally perturbed by no additional noise was intentionally added, but it can be corrupted by these types of noise during its acquisition process.

Conclusions

In this work we pointed out the advantage of using the Stationary Wavelet Transform over the Discrete Wavelet Transform. The percentage of well classified ECG signals in the case of SWT based algorithm are higher than in the case of DWT based algorithm, for each type of ECG signals tested. A maximum classification percentage was obtained for ECG perturbed by electrode motion artifact. The method is suitable to analyze non-stationary signals, especially biomedical signals, like the ECGs. The wavelet transform offers an alternative method to classical Fourier transform. Another advantage of our method is that it is less time consuming, even for long-term signals.

As a futures work a new research could be done in order to find out if other ECG records from the same database determine the same behavior of the classifier or to apply a denoising technique for the ECG record '108' used in this work.

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