Identification of cardiac arrhythmias by means of Wavelet Packet-based features

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Abstract

Cardiac arrhythmias are important indicators of heart diseases, they refer to electrical conduction problems and therefore their diagnosis is of high clinical interest. However, timely detection is difficult due to factors such as computational cost, large amount of heartbeats per record, morphology variability, infrequency and irregularity of pathological heartbeats. In this work, wavelet transform computed through wavelet packets is applied over electrocardiographic (ECG) signals as a method to characterize and identify normal ECG signals and some arrhythmias such as atrial fibrilation (AF) and life threaded arrhythmias, drawn from MIT databases.

Keywords: ECG, Atrial Fibrillation, Wavelet Packet, Energy

1. Introduction

Cardiovascular diseases are the main cause of death in the world. According to World Health Organization, in 2015 around 20 million people will die for this reason and this tendency will continue. Arrhythmias are one kind of cardiovascular pathologies typically caused by artery damage, electrical conduction problems and heart failure. One of the most frequent arrhythmias is atrialfibrilation (AF) [1]. AF affects around 1% of the general population and this percentage increases according to age, affecting to 12% of the population older than 75 years [2]. One of each six brain-vascular accidents occurs on AF diagnosed patient [3].

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Detection of AF has been addressed in previous works using techniques based on Wavelet and Wavelet Packet Transforms [4], and signal averaged P-wave analysis [5] with a maximum sensitivity of 91% and specificity of 83.5% as maximum value. Shuming and Huang [6] developed a method for detection of transitions between AF and Normal Sinus Rhythm (NSR) obtaining a sensitivity of 96,1% and specificity of 98,1%. However, computational cost is increased during peak detection, AF classification and histogram analysis.

In this work, features obtained from Discrete Wavelet Packet Transform are studied to characterize arrhythmias, such features are calculated over each level of decomposition and can give successful information of atrial activity by employing just one channel. Then, this characterization is useful for ECG signal analysis where the number of channels is small. Considered features are wavelet energy and its standard deviation for eight decomposition level. Experimental setup was done using ECG recordings from MIT databases [7].

Approach here presented is advantageous in comparison with traditional discrete and adaptive wavelet transforms because processing speed increases when implementing constant high-pass and low-pass filters to achieve a balanced decomposition. In addition, it is only necessary to use the first decomposition levels and one ECG lead or channel. Another advantage is the capability to carry out an analysis process with few data from recording whereas another wavelet based techniques can require more than five minutes of signal [4]. Proposed approach allows to identify normal and arrhythmia recordings in a short period of time, improving the time for diagnosis. This computational cost improvement may permit to implement fast diagnosis algorithms in mobile Holter embedded devices, that in addition to record data, detect and give information about the beginning of AF, allowing to prevent the development of cardiomyopathies or perform exercises for heart rate stabilization.

2. Materials and Methods

2.1. Discrete wavelet transform

Given a signal $s(t)$, its corresponding wavelet transform is given by:

$$W(a,b) = \frac{1}{a}\int_{\infty}^{+\infty} s(t)\psi(\frac{t-b}{a})dt \tag{1}$$

where $\psi(t)$ is the wavelet mother function and is chosen according to the nature of signal.

Discrete wavelet transform can be implemented by using two finite impulse response filters (FIR), high-pass filter (HPF) and low-pass filter (LPF), associated with the mother wavelet function and the wavelet scaling function respectively. Discrete impulse response of low-pass and high-pass filter are respectively represented by $h(k)$ and $g(k)$, where k denotes the k-th time instant. For instance, Haar wavelet filters are shown in Fig. 1.

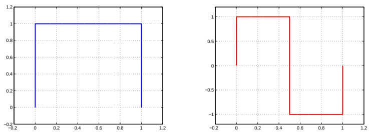

Figure 1: Haar Filter for $k = 1$: Scale function and Mother Function

2.2. Adaptive wavelet packet transform

Adaptive wavelet packet transform (AWPT) uses functions and filters to be calculated afor each level, Low pass filter is associated with scale function $\phi(x)$ and high pass filter with wavelet mother function $\psi(x)$. For the filters response of Fig. 1, the scale and mother function are define by:

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2 \\ -1 & 1/2 \le t < 1 \\ 0 & \text{otherwise} \end{cases} \qquad \phi(t) = \begin{cases} 1 & 0 \le t < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$h[k] = \left[\frac{\sqrt{2}}{2}, \frac{\sqrt{2}}{2}\right] \qquad g[k] = \left[\frac{\sqrt{2}}{2}, -\frac{\sqrt{2}}{2}\right]$$

Wavelet transform returns an unbalanced tree whereas Wavelet Packet with additional processes applied on high frequency achieves a balanced tree. Adaptive filters have coefficients that change and are adjusted to morphology along the signal. AWPT chooses the best representation through a adaptive search [4]. Approximation and detail coefficients are yield from LPF and HPF through a decimated convolution as follows:

$$Z_{1,0}(i) = s(i) * h(i) = \sum_{t=0}^{N-1} s(t)h(i-t) \tag{2}$$

$$Z_{1,1}(i) = s(i) * g(i) = \sum_{t=0}^{N-1} s(t)g(i-t) \tag{3}$$

where $s(i), i = 0, \ldots, N-1$ and N is the signal vector length.

To start the iterative decomposition, functions h and g have length $2N$ and are directly related with wavelet mother function. Then, wavelet functions W_{2n} and W_{2n+1} associated with detail and approximation coefficients can be computed iteratively using:

$$W_{2n}(x) = \sqrt(2) \sum_{k=2}^{2N-1} h(k)W_n(2x-k); W_{2n+1}(x) = \sqrt(2) \sum_{k=0}^{2N-1} g(k)W_n(2x-k) \quad (4)$$

where $W_0(x) = \phi(x)$ and $W_1 = \psi(x)$ ranged into the interval $[0, 1]$.

3. Experimental Setup

3.1. Signals and Feature Set

ECG signals were drawn from MIT databases, namely, MIT-BIH arrhythmia, MIT-BIH atrial fibrilation and MIT-BIH normal sinus rhythm [8].

† **MIT-BIH Arrhythmia:** contains 48 half-hour excerpts of two channel ambulatory ECG recordings, the records were digitalize at $360Hz$, with $11-bit$ resolution over a $10-mV$ range. The records were extracted both random and supervised from over 4000 original 24 hour records. 23 out of the 48, were chosen randomly to server as a representative sample to identify the variety of the waveforms, remaining 25, were supervised included because features of the rhythm, QRS morphology variation, or signal quality may be expected to present significant difficulty to arrhythmia detectors.

† **MIT-BIH Atrial Fibrilation:** individual recordings are each 10 hours in duration, and contain two ECG signals each sampled at $250Hz$ with 12-bit resolution over a range of 10 millivolts. The 23 records were extracted according to the presence of paroxysmal atrial fibrilation.

† **MIT-BIH Normal Sinus Rhythm:** this database includes 18 long-term ECG recordings. Each record contains a two channel signal, digitalizes at $128Hz$ with a $12-bit$ resolution.

For the first two databases, selected population were 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years. With two of the recordings coming from the same male subject. Subjects included in normal sinus database were found to have had no significant arrhythmias; they include 5 men, aged 26 to 45, and 13 women, aged 20 to 50.

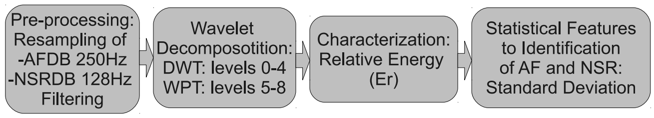

Figure 2: Schematized Experimental Setup

3.2. Preprocessing stages

First one consists of the resampling of the AF and NSR databases to $360Hz$ in order to compare results between them, since spectral information should be analyzed in the same frequency range. Since arrhythmia downsampling database leads to lost information whereas oversampling of AF and NSR databases add redundant information to the signal. In this context, sampling frequency was set $360Hz$ that also facilitates to filter the 60-Hz noise.

3.3. Wavelet based features

Haar mother function was chosen by means of a heuristical search, taking into account discrimination capability for considered arrhythmias. In addition,the square wave has a lower frequency selectivity. DB4 and DB6 are also good alternatives because of their geometrical similarity with ECG that supports a good convolution, however, the non-selectivity approach of haar filters allows to decompose signal in levels with balanced frequencies (wavelet decomposition tree). Then, this was the decisive criterion for the selection of the wavelet mother function.

3.3.1. Signal energy

As a feature, relative energy can be computed as follow:

$$E_{m,n} = \frac{\sum_{j=1}^{\ell_{m,n}} z_{m,n}^2(j)}{\sum_{j=1}^{\ell_m} z_m^2(j)} \tag{5}$$

where $\mathbf{z}_m$ represents all coefficients associated with level m, $\ell_{m,n}$ and ℓ_m are the number of elements of $\mathbf{z}_{m,n}$ and $\mathbf{z}_m$, respectively.

Relative Energy is related with the signal frequency, so it must be present in sub-bands of relevant frequencies. Normal rhythm has regular variability, with frequency ranged in 1,2 Hz - 1,4 Hz, moreover AF allows observation of “f” waves instead of “p” waves [4], with frequencies of 6 and 12 Hz for large-wave and small-wave.

3.3.2. Wavelet decomposition

We studied relative energy of eighth WP level (8,0 to 8,15). In order to determinate informative wavelet sub-bands associated with frequencies between 1Hz - 22.5Hz, wavelet mother function was scaled with regards to frequency [4]. For Haar wavelet, AF frequencies are located in sub-band 4,0 (0 - 22,5Hz), and was confirmed with a periodogram wich shown high spectral density (dB/Hz) in 0Hz to 22,5Hz sub-band.

To reduce computational cost, instead of WP decomposition, sub-band $(4,0)$ was obtained from the fourth level of DWT approximation coefficients, called $s'(i)$. Next step consist in extracting the fifteen sub-bands of the eight WP level in the original signal $s(i)$, through the fourth level WP decomposition of $s'(i)$.

3.3.3. Statistical features

As a statistical measure of the energy dispersion, standard deviation was extracted from the relative energy distribution of the level and sub-bands of the wavelet decomposition tree associated with frequencies of interest.

4. Results and discussion

The unbalanced nature of the decomposition tree generated by the discrete wavelet transform (DWT) causes that the analysis or study the energy distribution of the signal is unfeasible. On the other hand, by using the balanced tree returned by the AWPT allows to identify energy distribution for each sublevel index. Fig. 3 shows the structural difference between balanced and unbalanced decomposition trees.

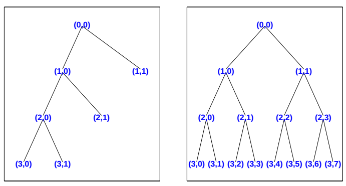

Figure 3: Decomposition Tree ($k = 3$):Unbalanced by DWT, Balanced by the AWPT

Analysis of the relative energy distribution in the $(8,0)$ to $(8,15)$ sub-bands shows that these sub-bands contains major concentration than the remaining and changes in the signal characterization. From the overall set of recordings, distinctive sets were chosen to show some results, for both arrhythmia and atrial fibrilation databases.

Figure 4 show the summarized mean energy distribution for selected patiens , from $(8, 0)$ to $(8, 15)$ sub-bands of Wavelet decomposition. It can be seen that the energy for the AF and arrhythmia signals is concentred in the sub-level $8, 0$, and this value presents a major drop in the case of normal sinus rhythm.

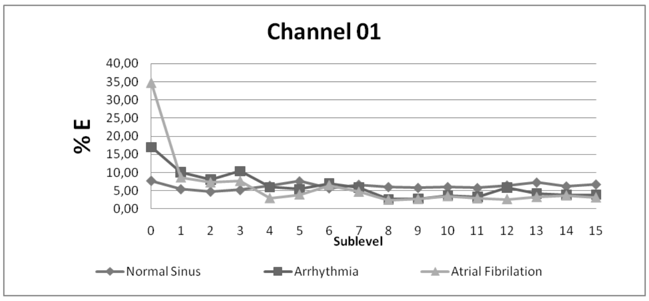

Figure 4: Energy distribution for the eighth level, ECG Channel 01

Statistical analysis was carried out using standard deviation over the obtained energy distribution. In normal sinus rhythm signals, the standard deviation of the eighth level energy distribution is found between 1% and 3% whereas for arrhythmias and atrial fibrilation is around 5% and 8%, respectively. Energy analyzed between sub-bands (6, 2) to (6.4), ECG Channel 1 sensitivity and specificity were between 60% and 95% and 57% and 94% respectively. The maximum computational cost was 0.2 MHz, equivalent to a fraction of the processing power of devices as cell phones or embedded Holter systems.

5. Conclusions

Efficient detection pathologies from normal signals is possible employing Wavelet Packets decomposition, and simple statistical parameters such as standard deviation of the distributed relative energy.

Spectral approach from the wavelet coefficients makes possible an ECG analysis regardless chosen channel, since information is not dependant of the signal morphology or amplitud, but still relating with frequency. Also, it was presented an approach to determine pathology existence, through a filter bank which is, in contrast to adaptive techniques, computationally more efficient. We propose as a future works to analyze and compare another parameters such as entropy, at different decomposition levels and filtering during preprocessing stages assessing the spectral information of the signal.

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