Efficient HRV analysis using wavelet package transform

Gley Kheder, Abdennaceur Kachouri and Mounir Samet

Abstract—In this study we are interested in the feature extraction of HRV which includes Ventricular Fibrillation (VF) and ventricular tachycardia (VT). Since the DWT analysis of the HRV causes frequency decomposition, in this study we are going to present a new solution using WPT to decompose the HRV signal into HF and LF frequency ranges. The 6 levels decomposition of WP provides high resolution. The obtained frequency bands are too close to LF and HF bands. RMS measure the signal power contained in the specified frequency bands LF and HF. The index of sympathovagal balance (LF/HF) was examined by RMS of wavelet coefficients. The LF/HF ratio gives a significant difference and efficient measurement of energy variations in both bands LF and HF by using standard deviation.

Keywords—Wavelet Package, Feature extraction, Heart Rate Variability, Sympathovagal balance.

I. INTRODUCTION

An electrocardiogram (ECG) is an electrical signal that represents the heart’s cardiac activity. This signal is recorded by means of certain number of electrodes which are pasted on the body. The typical ECG is constituted by P, QRS and T waves. The P wave corresponds to the atrium’s depolarization. The QRS complex results from the ventricular depolarization. The T wave corresponds to the polarization of the ventricle [1].

In this study we are interested on the RR intervals. RR intervals are defined by the time between successive R-waves. Thus, RR tachogram variability is essential for heart function’s measure. Variations’ analysis of this tachogram is known as Heart Rate Variability (HRV) analysis [2]–[3].

The parameters extracted from Heart Rate Variability signal used in assessing Autonomous Nervous System (ANS), HRV, described by the extraction of the physiological rhythms embedded within its signal, is the tool through which adaptations of activity of the ANS have been widely studied. In this study we are interested in the feature extraction of HRV which includes Ventricular Fibrillation (VF) and ventricular tachycardia (VT). The VF and VT are life-threatening cardiac arrhythmias. The exact detection and classification of these cardiac anomalies can diminish the rate of mortality from such cardiac diseases. While VT is represented as a series of three or more repetitive complexes that originate from the ventricles, is defined as three or more ventricular extra systoles in succession at a rate of more than 120 beats/min. However VF which is usually defined as a primary cardiac event is the commonest arrhythmia that causes sudden death out of hospital.

The measurement of the HRV’s non-stability presents a challenge to the signal processing techniques, especially in the dynamic conditions of functional testing [4]. The most common mathematical used to analyse HRV is the Fourier transform, which is limited to stationary signal. The best transformation of the signal expansion is to localize a given basis functions in time and in frequency. The limits of Fourier Transform, while analyzing the functions used are infinitely applied the Wavelet Transform (WT). This transformation is the most efficient method to quantify HRV in non-stationary conditions [4]–[6]–[7]–[8]. In our precedent studies we had to use DWT to analyse the HRV, but we encountered frequency decomposition problem [10]. This paper presents new solution using the wavelet package transform (WPT) to decompose the HRV signal into HF and LF frequency ranges.

II. METHODS

A. HRV analysis

The nervous system’s sympathetic branch increases the heart rhythm resulting in shorter beat intervals whereas the parasympathetic branch decelerates the heart rhythm leading to longer beat intervals. The spectral analysis of the HRV has led to the identification of two fairly distinct peaks: high (0.15-0.5 Hz) and low (0.05-0.15 Hz) frequency bands. Fluctuations in the heart rate, occurring at the spectral frequency band of 0.15-0.5 Hz, known as high frequency (HF) band, reflect parasympathetic (vagal) activity, while fluctuations in the spectral band 0.05-0.15 Hz, known as low frequency (LF) band are linked to the sympathetic modulation, but includes some parasympathetic influence (sympathetic-vagal influences)
[10]. In fact, the level of physical activity is clearly indicated in the HRV power spectrum.

For its analysis are used widely wavelets, these problems limit process ability and investigations can be canalized different points. Both of these this bands LF and HF energy frequency bands shift to unwanted frequency regions when DWT is used to determine them. This is very important for determination and interpretation of sympathovagal balance (LF/HF) [11]. In this work, WP is needed to move frequencies in between required bands.

B. Dataset

The dataset used in this study is obtained from physioBank entitled "Spontaneous Ventricular Tachyarrhythmia Database" [12]. This database contains 135 pairs of RR interval time series, recorded by implanted cardioverter defibrillators in 78 subjects. Each series contains between 986 and 1022 RR intervals. One series of each pair includes a spontaneous episode of ventricular tachycardia (VT) or ventricular fibrillation (VF), and the other is a sample of the intrinsic (usually sinus) rhythm. The ICD maintains a buffer containing the 1024 most recently measured RR intervals. Sampled signals are interpolated using cubic spline interpolation and resampled in 4 Hz.

C. Wavelet theory

A wavelet family \( \psi_{a,b}(t) \) is the set of elemental functions generated by dilations and translations of a unique admissible mother wavelet \( \psi(t) \).

\[

\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t - b}{a}\right)

\]

The discrete wavelet transform (DWT) achieves this parsimony by restricting the variation in translation and scale, usually to powers of 2. When the scale is changed in powers of 2, the discrete wavelet transform is sometimes termed the dyadic wavelet transform. Discrete wavelet function can be described by (1)

\[

\psi_{m,n} = 2^{-m/2} \psi(2^{-m} t - n)

\]

Here \( m \) is related to \( a \) as: \( a = 2^{m} \); \( b \) is related to \( n \) as \( b = n 2^{m} \) and \( m, n \in Z \).

The wavelet computations are equivalently performed simply using the filtering processes as

\[

\phi_{m+1,n}(t) = \frac{1}{\sqrt{2}} \sum_{k} c_{k} \phi_{m,2n+k}(k),

\]

\[

\psi_{m+1,n}(t) = \frac{1}{\sqrt{2}} \sum_{k} b_{k} \psi_{m,2n+k}(t),

\]

Where \( \phi(t) \) is scaling function, \( \psi(t) \) is wavelet function, \( c_{k} \) are scaling coefficients, \( b_{k} \) are wavelet coefficients, and \( k \) is location index of transform coefficients. Approximation and detail coefficients can be formulated respectively as

\[

G_{m+1,n} = \frac{1}{\sqrt{2}} \sum_{k} c_{k} A_{m,2n+k} = \frac{1}{\sqrt{2}} \sum_{k} c_{k-2n} A_{m,k},

\]

\[

H_{m+1,n} = \frac{1}{\sqrt{2}} \sum_{k} b_{k} A_{m,2n+k} = \frac{1}{\sqrt{2}} \sum_{k} b_{k-2n} A_{m,k}.

\]

Approximation (A) and detail (D) components is obtained with reconstruction of approximation and detail coefficients as

\[

A_{M}(t) = G_{M,0} \phi_{M,0}(t),

\]

\[

D_{m}(t) = \sum_{n=0}^{2^{M-m}-1} H_{m,n} \psi_{m,n}(t).

\]

Where \( M \) is last decomposition level.

A M-level decomposition of orthogonal wavelet basis is illustrated in Fig. , that is, detail coefficients at all the M levels (D1, D2..., DM) and approximate deepest decomposition level (AM). Approximate coefficients often resemble the signal itself.

Initial signal \( X \) is reconstructed as

\[

X = A_{M}(t) + \sum_{m=1}^{M} D_{m}(t),

\]

Wavelet packet (WP) transform are a generalization of DWT. In WP signal decomposition, both the approximation and detail coefficients are further decomposed at each level. In DWT, detail coefficients are transferred down, unchanged to the next level. However, in WP, all coefficients are decomposed in each stage. WP function includes third additional index as \( j \) and is described as

\[

W_{m,j,n}(t) = 2^{-j/2} W_{j}(2^{-m} t - n),

\]

Where \( j \in N \) denote node index in each \( m \) level [13].

D. Wavelet packet feature extraction

Feature extraction is a transformation of a pattern from its original form to a new form suitable for further processing. The first step in performing the feature extraction process should wavelet domain in mapping the data of distorted signal [13].

Wavelet packet decomposition at level \( j \) of HRV signal give \( 2^{j} \) sets of sub-band coefficients of length \( N/2^{j} \). The total number of such sets located at the first level to the \( j \)th level inclusive is \( (2^{j+1} - 2) \). The order of these sets at the \( j \)th level is \( m=1,2, ..., N/2^{j} \). Then, each set of coefficients can be viewed as a node in a binary wavelet packet decomposition tree. Wavelet packet coefficient, \( \{P_{m,j,n}(k) \mid k=1, 2, ..., N/2^{j}\} \), correspond to node \( (j,m) \). These vectors reflect the change of the signal with time in the frequency range of \( \left[(m-1)F_{s}/2^{j+1}, mF_{s}/2^{j+1}\right] \), where \( F_{s} \) is the sampling frequency [14].
There are many wavelets that can be needed to analyse the distorted signal and extract the feature vector. In this work the Daubechies “db4” wavelet function is used to analyse the signal by WPT. In fact, we obtained maximum energy localization using db4 and db8 when compared to the other type of wavelets [13].

The 6 levels decomposition of WP provides high resolution. The obtained frequency bands are too close to LF and HF bands. The resultant resolution of a terminal node is (6,r), r=0, 2, ..., 63. The LF band is localized in the nodes (6,1), (6,2), (6,3) et (6,4). However HF band is localized in the nodes (6,5), (6,7), (6,8), (6,9), (6,10), (6,11), (6,12), see Table I.

HRV produce variations in the relative energy associated with the different frequency bands and in their degree of importance. RMS (Root Mean Square) measure the signal power contained in the specified frequency band LF and HF. The index of sympathovagal balance (LF/HF) was examined by RMS of wavelet coefficients used (12).

Wavelet package energy is determined depending on $w$ values that is obtained reconstruction of $W_{m,j,n}$.

$$e(m, j) = \sqrt{\frac{1}{N} \sum |W_{m,j}(r)|^2}$$  \hspace{1cm} (11)

$e(m, j)$ are RMS values of interested band.

$$\frac{LF}{HF} = \frac{e(6,1) + ... + e(6,4)}{e(6,5) + ... + e(6,12)}$$ \hspace{1cm} (12)

III. RESULTS AND DISCUSSION

The number of signals used in this simulation recorded from subjects with different ages (between 20 and 75 years old). Among which, 29 signals are normal used as control groups, the two other signal groups (of 29 signals) are respectively VT and VF arrhythmias.

Fig. 1 presents an efficient analysis of sympathovagal balance variations. The domination of sympathetic activity is well detected when this is higher than 2.1. If this ratio is smaller 1.4, it denotes domination of parasympathetic activity. These two activities are well detected while analysing the VT and VF signals by means of WP.

The variations of the ratios, measured by means of wavelet coefficients energy, of the signals with VT and VF anomalies gives significant differences (p<0.0002) in accordance with normal signals.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>THE FREQUENCY RANGES WITH RESPECT TO NODES</th>
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<tbody>
<tr>
<td>HRV Bands</td>
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<tr>
<td>LF</td>
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Fig. 1 Variation of SB

Fig. 2 Standard deviation form VF arrhythmias and controls in LF ranges

Fig. 3 Standard deviation form VT arrhythmias and controls in LF ranges
variation of the wavelet coefficients using the standard deviation of the LF band in the signals with VT and VF arrhythmias, we note that when the role of the parasympathetic nervous system marked by variation in the LF band is prevalent, the sympathetic and parasympathetic nervous systems play a role in the development of the LF as efferent nerves of the autonomous nervous system.

Fig. 4 Standard deviation form VF arrhythmias and controls in HF ranges

Fig. 4 and Fig. 5 show the standard deviation of wavelet packet coefficients at the frequency ranges HF of HRV with VT and VF arrhythmias. A change in standard deviation in the wavelet packet coefficients corresponds to a change in signal power at that frequency range. We consistently observed that the standard deviation of the sympathetic activity of the subjects with VT and VF arrhythmias as increases as compared to the respective standard deviations of the control groups.

IV. CONCLUSION

In this paper, we have presented HRV analyse using wavelet package transform. The wavelet packet utilized an optimized division. The wavelet packet analysis is a flexible approach, because the division of the frequency spectrum can be regular performed schemes. Wavelet package transform has been made to adapt to the signal characteristics by calculating an optimized decomposition for the whole HRV time series.

WP give an efficient extraction of the two frequencies ranges LF and HF. RMS measure the signal power contained in the specified frequency band LF and HF. We obtained maximum energy localization using “db4” wavelet function. The feature vector as constructed by the ratio LF/HF and the standard deviation of wavelet coefficients.

REFERENCES


Gley Kheder was born in Gafsa, Tunisia in 1978. He received the electrical engineering degree in 2002 and Master degree in electronics and telecommunication in 2003, both from National School of Engineers of Sfax, Tunisia (ENIS). She currently is working toward the Ph.D. degree in electronic at the same school. Her research interest is to feature extraction of the electrocardiogram using signal processing technique.

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