Wavelet transform based HRV analysis

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Abstract

Heart rate variability (HRV) is a measure of variations of the successive heart beats. It is usually calculated by analyzing the time series of beat-to-beat intervals from ECG signal. HRV is considered as an indicator of the activity of autonomic regulation of circulatory function and as the one of the most significant methods of analyzing the activity of the autonomic nervous system. In this study a Wavelet Packet Transform (WPT) based HRV feature extraction method is presented and compared with the Fourier transformed based one. The results show that a good WPT decomposition gives a significant index of sympathovagal balance, which is the variance (or power) of the ECG signal changes as a function of frequency.

Keywords: heart rate variability, wavelet packet decomposition, subband analysis

1. Introduction

The Electrocardiogram (ECG) is a time-varying signal measured on skin surface which reflects the electrical activity of the heart. The ECG signal is obtained by recording the potential difference between two electrodes placed on the body surface. A single normal cycle of the electrocardiogram means the successive atrial and ventricular depolarization/repolarization represented by specific shapes, intervals and duration in recorded ECG signal.
1.1. Heart Rate variability

Heart rate variability (HRV) is a measure of the time series of beat-to-beat intervals from ECG which are defined between successive R-waves (notated also with N, meaning normal beat) as local maxima corresponding to the ventricular depolarisations. In the last few years HRV acquired an extreme interest in almost all branches of contemporary medicine. It is proved that the unfavorable changes in HRV could be used as a predictor of wide range of life-threatening diseases [3].

HRV can be measured in time or frequency domains. Time domain methods are usually the simplest to perform and mean the calculations of standard deviation of the N-N intervals (SDNN, representing the overall HRV), the number of adjacent N-N intervals that differ by more than 50 ms (NN50), the square root of the mean squared differences between adjacent N-N intervals (RMSDD) and the standard deviation of the average N-N interval over periods of about 5 min (SDANN).

Spectral methods usually measure how the variance (or power) of the ECG signal changes as a function of frequency. A common frequency domain method is the calculation of the Discrete Fourier Transform through the Fast Fourier Transform, to the beat-to-beat interval time series. That expresses the amount of variation for different frequencies. Several frequency bands of interest have been defined in humans. High Frequency band (HF) is defined between 0.15 and 0.4 Hz. HF is driven by respiration and appears to derive mainly from vagal activity or the parasympathetic nervous system.

Low Frequency band (LF) is defined between 0.04 and 0.15 Hz. LF derives from sympathetic activity and has been hypothesized to reflect the delay in the baroreceptor loop.

Very Low Frequency band (VLF) band between 0.0033 and 0.04 Hz is also defined. The origin of VLF is not well known, but it had been attributed to thermal regulation of the body’s internal systems.

This paper focuses on spectral method in order to identify the energy distribution of HRV signal in the mentioned frequency bands using wavelet packet decomposition technique in order to compute the sympatovagal index as the . The results can be compared with other values obtained using the FFT method.
1.2. The wavelet transform

The continuous wavelet transform (CWT) of the signal $x(t)$ is defined as a convolution of the signal with a scaled and translated version of a base wavelet function, [1]: [3]: The wavelet transform (WT) of signal $x(t)$ is defined as a combination of a set of basis functions, obtained by means of dilation $a$ and translation $b$ of a mother wavelet [1]:

$$W_x(x) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \psi \left( \frac{t-b}{a} \right) dt \tag{1}$$

The discrete wavelet transform (DWT) is defined as a discretized dilations and translations of the mother function, (or analyzing wavelet). In its most common form, the DWT employs a dyadic grid (integer power of two scaling in $a$ and $b$) and orthonormal wavelet basis functions and exhibits zero redundancy.

$$\psi_{(s,l)}(x) = 2^{-s/2} \psi(2^{-s} x - l) \tag{2}$$

The variables $s$ and $l$ are integers that scale and dilate the mother function $\psi$ to generate wavelets (analyzing functions). The scale index $s$ indicates the wavelet's width, and the location index $l$ gives its position. The mother wavelets are rescaled, or "dilated" by powers of two, and translated by integers, in this case we have a dyadic decomposition structure. The Discrete Wavelet Transform decomposition of the signal into different frequency bands (according to Mallat’s algorithm [2]) can be obtained by successive high-pass and low-pass filtering (digital FIR structures) of the time domain followed by downsamplig to eliminate the redundancy, as shown in Fig. 2.

Given a signal, a low-pass and high-pass (using two quadrature mirror filters), half-band filtering is performed on it, obtaining two sequences. Having already done a half-band filtering, one can subsample the new sequences by a factor of two, following the Nyquist theorem. The process is iterated on the low pass signal as long as needed. Fig. 3 shows a third level decomposition structure for a given data signal with the corresponding bandwidths[3].

Wavelet packet analysis is a generalization of wavelet analysis providing a redundant decomposition procedure, using these basic equations
Both detail and approximation signals are split at each level into finer components. A set of details and approximations is called the wavelet packet decomposition tree, as in Fig. 3

\[
\phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} h_k \phi(2t + k), \quad \psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} g_k \phi(2t + k)
\]

(3)

As we can see this dyadic division of the bandwidth could be the key of subband processing techniques which allow independent processing in these subbands. In this case these subbands become important from a frequency domain view, because they have a certain value, a dyadic divided part from the original bandwidth.

Fig. 4. Filter bank structure of DWT and WPT for a third level decomposition (resulting nodes)
2. Material and methods

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) [3]. It is known that the level of physical activity is clearly indicated in the HRV power spectrum. The dataset used in this study is obtained from so called PhysioBank database, entitled "Long Term ECG Database" [12].

The proposed procedure is presented on Fig. 5. The R-R interval time series are interpolated and resampled, at constant level of signal energy, in order to have a convenient sampling rate. The Wavelet Packet (WP) decomposition at level $j$ of HRV signal offers to study $2^j$ sets of sub-band coefficients of length $N/2^j$. If the sampling rate is 5Hz, a 6th level WP decomposition offers the nodes $N(6,i)$, with $i=0...63$. The resampling must be done after an interpolation in order to keep unmodified the main characteristics of the signal, also the energy of the signal. The primary sampling frequency is computed as the double value of minimum rounded-up rate of the signal. The main task during the interpolation and resampling phases is to keep unmodified the energy of analysed signal.

The 6th level WP decomposition provides high resolution through the 64 frequency ranges. These are close enough to the defined low frequency (LF) and high frequency (HF) bands. The resultant resolution of a terminal node is $N(6,r), r=0, 2, ..., 63$. The LF band is localized in the nodes $N(6,1), N(6,2), N(6,3)$, meaning the 0.039 – 0.156 Hz frequency range, similarly HF band is localized in the nodes $N(6,4), N(6,5), N(6,6), N(6,7), N(6,8), N(6,9), N(6,10)$ as in Table 1. RMS (Root Mean Square) measure the signal power contained in the specified frequency band LF and HF.

Table 1 The frequency bands corresponding to the 6th WP decomposition

<table>
<thead>
<tr>
<th>HRV frequency bands</th>
<th>WPT Nodes</th>
<th>Correspondent frequency band</th>
</tr>
</thead>
<tbody>
<tr>
<td>LF (0.4 – 0.15Hz)</td>
<td>$N(6,0)$</td>
<td>0 - 0.0390625 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,1)$</td>
<td>0.0390625 – 0.078125 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,2)$</td>
<td>0.078125 – 0.117189 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,3)$</td>
<td>0.117189 – 0.156252 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,4)$</td>
<td>0.156252 – 0.195315 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,5)$</td>
<td>0.195315 – 0.234378 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,6)$</td>
<td>0.234378 – 0.312504 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,7)$</td>
<td>0.312504 – 0.351567 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,8)$</td>
<td>0.351567 – 0.390630 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,9)$</td>
<td>0.390630 – 0.429643 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,10)$</td>
<td>0.429643 – 0.468756 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,11)$</td>
<td>0.468756 – 0.507819 Hz</td>
</tr>
<tr>
<td></td>
<td>$N(6,63)$</td>
<td>2.490937 – 2.5 Hz</td>
</tr>
</tbody>
</table>

Fig.5. The proposed algorithm
The index of sympathovagal balance (LF/HF) is computed from wavelet coefficients as follows:

\[
\frac{E(6,1) + E(6,2) + E(6,3)}{E(6,4) + E(6,5) + E(6,6) + E(6,7) + E(6,8) + E(6,9) + E(6,10)}
\]

(4)

Where the correspond energy levels are computed as

\[
E(n, j) = \sum w_{n,j}^2
\]

(5)

Fig. 6 represents the energy distribution over the mentioned frequency ranges, obtained by the FFT of HRV sequences compared to the whole spectrum. In this case the energy distribution of these subbands can be computed and compared in order to obtain the LF/HF ratio.

3. Results

The wavelet packet decomposition leads to an exact localization of certain frequency bands, that localization doesn’t depend on signal’s lengths. Fig. 7 presents the energy component values for the considered frequency ranges obtained with the 6th level WP decomposition.

Fig. 7. The wavelet packet node’s energy distribution
The LF/HF index was computed both with 6th level WP decomposition and FFT based method. The signal were of different lengths and resolutions, from the mentioned database, the obtained results are synthesized in table 2.

<table>
<thead>
<tr>
<th>signal</th>
<th>length</th>
<th>LF/HF by FFT</th>
<th>LF/HF by WP</th>
</tr>
</thead>
<tbody>
<tr>
<td>14046</td>
<td>115278</td>
<td>0.868</td>
<td>0.787</td>
</tr>
<tr>
<td>14046_1</td>
<td>100000</td>
<td>0.657</td>
<td>0.604</td>
</tr>
<tr>
<td>14046_2</td>
<td>65536</td>
<td>0.871</td>
<td>0.731</td>
</tr>
<tr>
<td>14046_3</td>
<td>32818</td>
<td>0902</td>
<td>0.788</td>
</tr>
</tbody>
</table>

4. Conclusions

The most common mathematical method used to analyze 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 sharp in their frequency localization. They exist at one exact frequency but have no time localization. One of the major drawback of FFT method is the apparition of undesired frequency components if the signal’s length don’t satisfy the requirement to be a power of two. Wavelet domain HRV variables provide more specific information about autonomic activity. The WPT method was found to have good time-frequency resolution and give reasonable classification results which compare well with the other approaches.

References