

A Robust R Peak Detection Algorithm Using Wavelet Transform for Heart Rate Variability Studies

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Abstract: We propose in this work a method of electrocardiogram (ECG) signal pretreatment by the application of Discrete Wavelet Transform DWT by automatically determining the optimal order of decomposition. After the purification of the original signal, we describe an algorithm to detect R waves based on the Dyadic Wavelet Transform DyWT by applying a windowing process. This algorithm is validated on a sample of synthesis ECG signal with and without noise which we have proposed and on real data. Finally, once the R peaks of real data are detected, we use three methods of RR intervals analysis by calculating the standard deviation of heart rate and applying the Fast Fourier Transform FFT and the Wavelet Transform on detected RR intervals to study the Heart Rate Variability (HRV). A comparative study between the analysis results of detected RR intervals in healthy and diseased subjects through the application of the FFT and the Wavelet Transform will be given.

Keywords: electrocardiogram, R peaks, Wavelet Transform, Fast Fourier Transform, Heart Rate Variability.

1. Introduction

The detection of cardiac arrhythmias is a crucial point in the cardiac diseases diagnosis. An arrhythmia is characterized by the irregularity of the heart rate. A heart rate is regular if it is of the order of 60 beats per minute; otherwise, it's called bradycardia or tachycardia. The most commonly used modality for the arrhythmia diagnosis is the ECG. The detection of this cardiac irregularity is based on the R peaks detection and analysis of their regularity (RR intervals).

In this context, several studies have been conducted. For example, in the derivative based methods [1, 2, 3], to detect the R peaks, the authors use the first derivative (respectively second derivative in [2, 4]). They locate for this purpose, the complex QRS by the thresholding of the derivative. These works suffer mainly from two limitations: their sensitivity to noise and the choice of a threshold. Other works exploit nonlinear analysis methods, especially the neural networks [5, 6] and non-stationary analysis tools such as wavelets that are the most used [7, 8, 9]. Particularly in [7], for the QRS complex detection by Discrete Wavelet Transform, The authors have used different mother wavelets: Cubic Spline, Haar and Daubechies4 (Db4), where the choice of decomposition scale is empirical. They have shown that the best results are given by the Cubic Spline and the Db4 wavelets. Once the R peaks are detected, the diagnosis of cardiac arrhythmia passes through the analysis of the RR interval regularity. Several techniques are used, we can cite: the use of the FFT for the extraction of the frequency parameters to analyze the sympathetic and parasympathetic systems participation in the regulation of heart rate [10, 11]. The authors in [12] use statistical methods to analyze the RR intervals in the time domain. Other works [13] use wavelets to study Heart Rate Variability in both frequency and time domains.

The objective of this work is to propose a robust wavelet method to detect R peaks and compare different algorithms for RR interval analysis. Major interest of the recent paper is shed some light to the automatic calculation of optimal wavelet decomposition scale. In a first

step, to reduce the sensibility to the noise, we suggest to generalize the ECG signal pretreatment through the implementation of a bandpass filter which comprises a low pass filter based on DWT (Db2) and a high pass filter based on DWT (Db11). Our contribution is situated at this level in the determination of the decomposition level in an automatic manner basing on the sampling frequency and the bandwidth of the ECG signal for each of the used filters. Once the signal is purified, we proceed to the R peaks detection. In a second step, we propose to apply a windowing of the ECG signal in order to solve the problem of thresholding and false detections caused by the variability of the R peaks morphology. To validate our approach and test its robustness by a report to the noise ratio and the R peaks morphology, we will apply it first on synthetic data and then on real data which are relative to 10 subjects (healthy and pathological). A comparison of our results for the R peaks detection with those of other studies [2, 5, 7] will be given. Finally, for the RR intervals analysis of real data, we propose the use of three methods: the calculation of heart rate and standard deviation, the FFT and the Wavelet Transform.

2. Detection and Analysis of R Peaks

The detection and analysis of the R peaks method proposed in this paper is composed of three phases: pretreatment, detection and analysis (Figure 1).

- Pretreatment: the first phase consists in filtering the ECG signal by a high pass filter in cascade with a low pass filter.
- R peaks detection: the second phase consists in using the Wavelet Transform method to extract the R peak positions.
- R peaks analysis: finally, using as input the R peak positions, we aim to study Heart Rate Variability. We propose to use three different methods: Statistical analysis, FFT and Wavelet Transform.

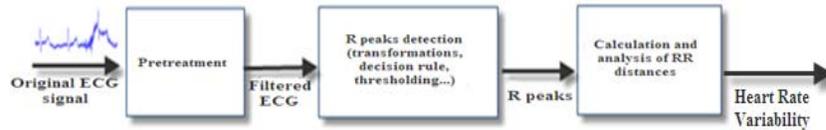


Figure 1. The block diagram of the automatic ECG Processing chain.

A. Wavelet Transform

The Wavelet Transform is a convolution of the wavelet function $\psi(t)$ with the signal $x(t)$. The Continuous Wavelet Transform CWT is defined by the Equation 1:

$$C(a,b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}(t) dt = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt \quad (1)$$

Where ψ is the mother wavelet, a is the scale factor and b is the translation parameter.

The scale factor a discretization and parameter b translation by an appropriate sampling grid is required to faster calculations. This discretization gives the Dyadic Wavelet Transform DyWT:

$$a = 2^j \quad b = k \cdot 2^j$$

$$DyWT_x^\psi(j,k) = C_{j,k} = 2^{-j/2} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-k}{2^j}\right) dt \quad (2)$$

Where j and k are two integers.

In the discrete case, the Wavelet Transform requires the decomposition and the reconstruction of the signal.

At the decomposition phase, the Wavelet Transform is modified to a filter bank tree using the multi-level decomposition by a low pass filter $h(n)$ and a high pass filter $g(n)$ (Figure 2) [14]. At each level, the signal is decomposed into two components: approximation (cA_j) and detail (cD_j). The former represents the general shape of the signal or low frequency

components. The later represents short and quick events or high frequency components. The approximation and details coefficients are respectively defined by Equations 3 and 4:

$$cA_{j+1}(k) = \sum_{n=-\infty}^{\infty} h(n-2k)cA_j(k) \tag{3}$$

$$cD_{j+1}(k) = \sum_{n=-\infty}^{\infty} g(n-2k)cA_j(k) \tag{4}$$

Where j is the decomposition level.

The reconstruction phase begins with the oversampling data followed by two reconstruction filters \bar{h} and \bar{g} to obtain the original signal as expressed by the equation 5.

$$x(t) = cA_j(k) = \sum_{n=-\infty}^{\infty} cA_{j+1}(n)\bar{h}(k-2n) + \sum_{n=-\infty}^{\infty} cD_{j+1}(n)\bar{g}(k-2n) \tag{5}$$

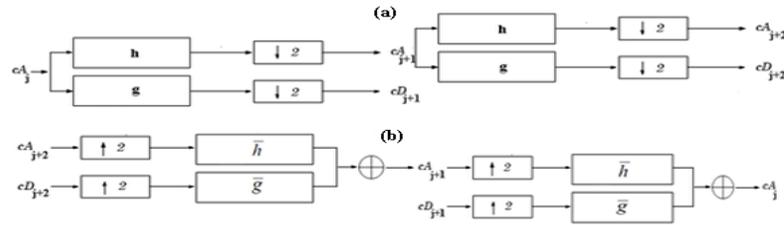


Figure 2. Filter bank trees of: (a) decomposition (DWT), (b) reconstruction (IDWT).

B. Step by step design method

B.1 Pretreatment of ECG Signals

During the recording of ECG signals, different types of noise from various sources (artifacts, calibration of the device, electrical activity of muscles ...) can be superimposed to the original signal. To purify the signal, many methods have been proposed: Adaptive filtering [15], digital filtering [16] and wavelet filtering [17, 18]. In particular, the authors in [17, 18] have used the Wavelet transform with an empirical scale factor.

Using the knowledge that wavelet filtering is efficient and accurate in the compute of the R peaks positions without change of the shape or position of the original signal, we propose to use this technique to filter the ECG signal. Our contribution is the automatically determination of the scale factor which optimizes the purification of the signal using two criteria: the signal sampling frequency and the knowledge that most of the noises are located at frequencies below 1.5 Hz and higher than 50 Hz [19].

For this purpose, we propose a band pass filter which is constituted by a high pass filter with cutoff frequency 1.5 Hz in cascade with a low pass filter which its cutoff frequency equals to 50 Hz. First, the application of high pass filter eliminates baseline variations. Then, the application of low pass filter removes high frequency noise (Figure 3).

The scale and type of the mother function parameters are specific to each filter. Thus, the automatic compute of optimal scale in the case of a sampling frequency of 256 Hz gives the order six for high pass filtering and order two for the low pass filtering.

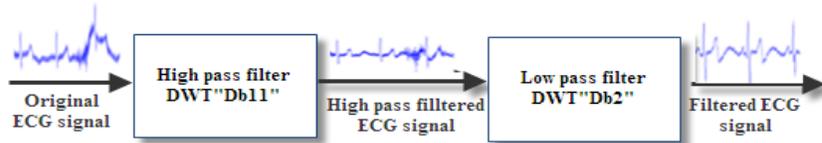


Figure 3. The block diagram of the ECG pretreatment phase.

For the choice of the mother function, we have achieved a comparative study using various types of mother functions: coiflet, symlet and Daubechies. The best results are obtained by the use of the Db11 mother wavelet in the case of high pass filtering and the Db2 wavelet in the case of low pass filtering.

The high pass filter is constituted by three stages (Figure 4). The first consists in decomposing the original ECG signal by DWT in its components of approximation and detail. The second consists in removing variations in the baseline generally characterized by low frequencies of the order of 0.1 Hz. The presence of these variations is seen for large orders of approximation coefficients of the DWT. Solving this problem requires setting to zero the last approximation coefficients. Finally in the third stage, we calculate the IDWT by using the new coefficients to reconstruct the signal where the variations of the baseline are eliminated (Equation (5)).

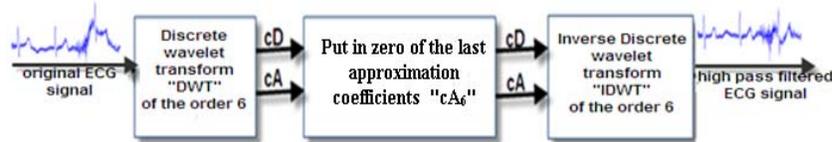


Figure 4. The low frequency filtering block diagram, cA are the approximation coefficients of DWT.

The low pass filtering process is constituted by four stages (Figure 5). The first consists in calculating the DWT to order 2 of the ECG signal to get the detail coefficients (Equation (4)). In the second step, we calculate the mean μ (Equation (6)) from the absolute values of the first detail coefficients $cD_1(k)$ then the standard deviation σ (Equation (7)).

$$\mu = \frac{1}{N} \sum_{-\infty}^{\infty} Abs(cD_1(n)) \quad (6)$$

Where N is the number of the detail coefficients cD_1 .

$$\sigma = \frac{\mu}{0.6745} \quad (7)$$

Where 0.6745 is an empirical value used to calibrate the mean with standard deviation for a Gaussian process [20].

The threshold value is obtained by Equation 8:

$$S = \sigma \sqrt{2Ln(N)} \quad (8)$$

The third step is to select the detail coefficients (cD) using Equation 9:

$$cD_iChang(k) = \begin{cases} cD_i(k) - sign(cD_i(k)).S & \text{if } cD_i(k) > S \\ 0 & \text{if } cD_i(k) \leq S \end{cases} \quad (9)$$

Finally, in the fourth step we compute the IDWT using the new coefficients to reconstruct the denoised signal (Equation (5)).

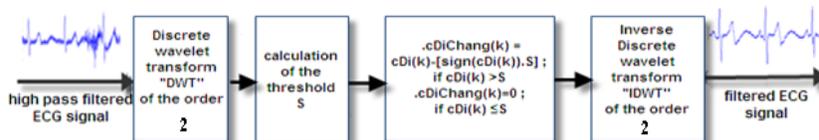


Figure 5. The high frequencies filter block diagram, cD_i is the detail coefficients of DWT.

With a sampling frequency of 256Hz, the selected frequencies range of the filtered signal varies in the range 2 Hz and 32 Hz.

B. 2. R Peaks Detection

As input we use a purified ECG signal. We aim to detect R peak positions. For this we have to resolve a key problem which is the R peak morphology variations (Figure 6). Using the hypothesis that on small intervals of time, the R peaks do not admit a large variability in its morphology, we propose to apply a time windowing on the ECG signal. The window allows the reduction of false detections when using small intervals of time.

For the R peaks detection, we propose the use of the DyWT for their ability to detect and locate accurately the waves. Similarly to the pretreatment, we apply the same process (B.1) to the scale compute and the mother function choice. As input, we have the QRS complex (Figure 8) whose frequencies vary between 5Hz and 15Hz, therefore a scale of order 4 and a choice of Db4 mother wavelet. The Db4 wavelet is very interesting for the detection and location of R peaks due to the strong resemblance of its model to the ECG signal. Our method is organized in the following steps:

- Step 1: We use as input a filtered ECG signal by the use of a band pass filter as described in (B.1), we calculate the DyWT of the ECG signal in the scale 2^4 ($j = 4$) using the Equation (2).
- Step 2: We initialize the window time to 4s. We calculate the total number N of windows throughout the ECG recording where N is obtained by :
 Time window =4;
 Total time=Total number of samples/ sampling frequency;
 Portion number=round(total time/window time);
- Step 3: For each window, we find the positive maxima and the negative minima of the DyWT by report in a threshold S1 (= 0.45 * max signal amplitude) and a threshold S2 (= 0.28 * min signal amplitude) respectively. This step determines the negative minima-positive maxima couples DyWT of the possible complex QRS.
- Step 4: having computed all possible QRS, it is now necessary to remove the redundant minima and maxima and the isolated couples. For this, we eliminate among two minima (respectively maxima), the farthest minimum (respectively maximum) from the maximum (respectively minima) of the couple. As output, we only obtain the closest negative minima- positive maxima couples which are the most likely to be the Wavelet Transform of the QRS complex.
- Step 5: We locate the R peaks of QRS complexes from different intervals limited by the negative minima-positive maxima couples by looking for the points in which the DyWT nullifies.
- Step 6: After calculating the P peak total number M and arranging all the M peaks in a single vector, we calculate the RR intervals between two successive R peaks as follows:
 $RR(j)=\text{peak position R}(j+1)-\text{peak position R}(j)$.

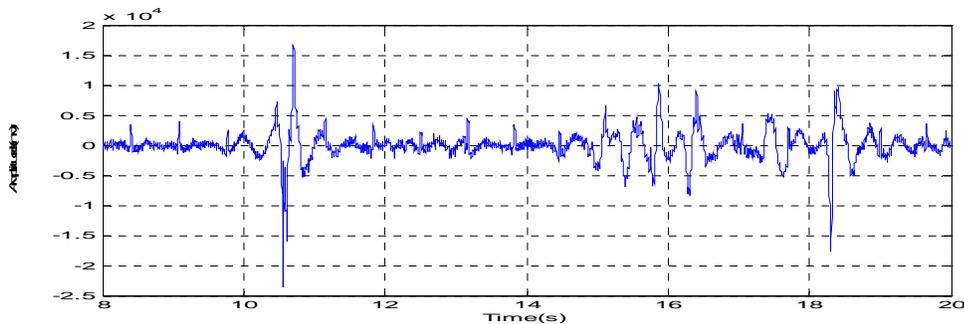


Figure 6. R peak morphology variations.

B.3 RR intervals Analysis

The RR interval analysis consists in studying the Heart Rate Variability (HRV). The HRV is a measure of the heart rate variations. It is usually calculated by analyzing the time series of beat to beat intervals from ECG (RR interval) or traces of blood pressure. It is obtained by measuring the time between RR intervals on the electrocardiogram. The values of RR intervals are then plotted versus time, giving a curve called tachogram of HRV or RR tachogram (Figure 7). This tachogram is a combination of sinusoidal waves of different frequencies.

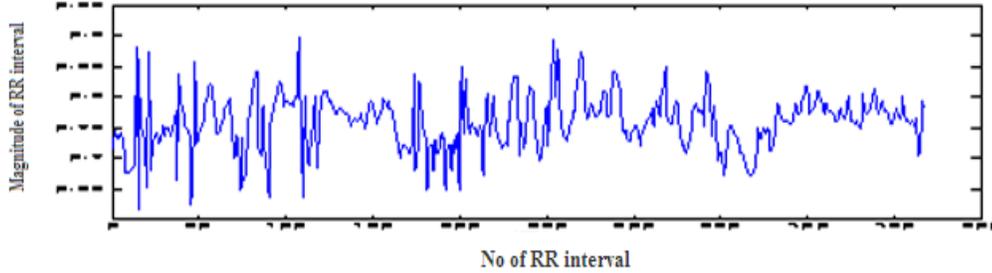


Figure 7. Tachogram of HRV.

There are various heart rate variability analysis, which can be subdivided into linear analysis (time and frequency) and nonlinear analysis (wavelet). The time domain methods are computationally simple, but lack the ability to discriminate between sympathetic and parasympathetic contributions of HRV. The studies of HRV employed the fast Fourier transform (FFT) for Power Spectral Density (PSD). A time-scale method developed in recent years allows studying these non stationary ECG signals: the wavelet method whose principle is to describe the evolution of a signal at different levels of temporal resolution [21]. The evolution of the frequency over time is thus particularly interesting for non-stationary signals. In this work, we chose to compare the RR interval analysis using the three following methods: Statistical analysis, FFT and Wavelet Transform.

Statistical Analysis

For the analysis of RR intervals, we interest primarily in the extraction of beat frequency (F) in beats per minute (beats / min or rpm). For the measure of this beat frequency, we need to have the average and the excursion of periods around this average: $F \pm \Delta F$ which we can deduce from the R peaks detection algorithm previously exposed.

The first parameter is derived from the developed R peaks detection algorithm by the following formulas:

$$\text{RR Distance: } RR_{mean}(S) = \frac{L.T_{samp}}{N_{QRS}} \quad (10)$$

$$\text{Beat frequency: } F(\text{beats / mn}) = \frac{60}{RR_{mean}(s)} \text{ or } F(\text{beats / mn}) = \frac{60.N_{QRS}}{L.T_{samp}} \quad (11)$$

With: L : total length of the recording (sample number).

T_{ech} : the sampling period (s).

N_{QRS} : Number of detected QRS.

ΔF is the value of the standard deviation which is the difference between the maximum value and minimum value of the RR interval:

$$\Delta F = \sqrt{E(F - \bar{F})^2} = \sqrt{\frac{1}{N} \sum_{k=1}^N (F - \bar{F})^2} \quad (12)$$

A rhythm is irregular if the frequency variation is greater than 10%.

Fourier analysis

The objective of using the FFT in the RR analysis is to address the regulation of the cardiac activity by the Autonomic Nervous System (ANS) in different situations. The FFT divides the RR intervals by extracting the sinusoidal waves that compose it. It expresses the amount of variation for different frequencies and displays the results in a spectrum of power density.

The Power Spectral Density describes how the power of a signal or time series is distributed with frequency. The function of Power Spectral Density shows the force variations as a function of frequency. In other words, it represents the variations of high and low frequencies.

In this representation, the total observed HRV is expressed in terms of total spectral power. The spectral representation is used to extract the total observed HRV from variability attributable to each of the sinusoids composing the spectrum. Thus, it is possible to calculate a power spectrum in a frequency band. For example, if the respiratory frequency is between 45 and 60 cycles per minute, the HRV of respiratory origin occurs in a frequency band between 0.7 and 1 Hz. The power spectrum in this band corresponds to the part of the HRV related to respiration, which is determined by a parasympathetic mediation.

The frequency variations are established between 0 and 0.4 Hz. The power spectrum of a high frequency (HF) is estimated in the range of 0.15 to 0.4 Hz [10]. The oscillation in this frequency band is known as the Traube-Hering waves. This band is led by breathing and appears to be mainly derived from a vagal activity (parasympathetic). It corresponds to the respiratory arrhythmia.

The power spectrum of a low frequency (LF) is estimated between 0.04 and 0.15 Hz [10]. The oscillation in this frequency band is known as the Mayer wave. There is a peak, usually around 0.12 Hz. This band is derived from the vagal and sympathetic activity and was supposed to reflect the delay in the baroreceptor loop. In fact, the heart rate oscillations in the LF area are related to the activity of the baroreflex system. Parasympathetic and sympathetic systems are both involved: when the activity of a system increases, the other decreases. The increase of the LF in the RR interval spectrum is often due to an activation of the sympathetic system. After the vagal blockade, there is an important decrease of low frequencies in the RR interval spectrum, which completely disappears after a beta-adrenergic blockade.

The Component of a very low frequency (VLF) is estimated in the range of 0.003 to 0.04 Hz [10]. It reflects the regulatory mechanisms in the long term, probably related to thermoregulation, vasomotor, the renin-angiotensin system or other factors. These rhythms are difficult to analyze with the traditional methods of the spectral analysis.

In this Fourier analysis, we are also interested in calculating the normalized low and high frequency power (LFnu and Hfnu) as $100 \cdot \text{LF} / (\text{total power} - \text{VLF})$ and $100 \cdot \text{HF} / (\text{total power} - \text{VLF})$, respectively, and the LF/HF ratio. This ratio represents an evaluation of the autonomic nervous system balance (sympathetic/parasympathetic). A decrease in this score might indicate either increase in parasympathetic or decrease in sympathetic tone.

Wavelet analysis

The decomposition of a signal by Wavelet Transform requires a mother function adequately regular and localized. The analysis amounts to sliding a window of different levels containing the wavelet function, all along the signal. The calculation gives a serial list of coefficients named wavelet coefficients, which represent the correlation evolution between the signal and the chosen wavelet at different levels of analysis all along the signal.

In our analysis, we have used the Db4 Wavelet Transform. For each recording, the wavelet coefficients were calculated on various RR Tachograms, giving seven separate levels of analysis named 2, 4, 8, 32, 64 and 128. Then, we have calculated the variability power, level by level, as the sum of coefficient squares. Thus, we have obtained, for each recording, the variability power for each level.

The sum of wavelet power coefficients at levels 2, 4, and 8 roughly corresponds to the Fourier high frequencies (an index of parasympathetic activity). The wavelet power coefficients at levels 16 and 32 approximately correspond to the Fourier low frequencies. The wavelet power coefficients at levels 64 and 128 correspond to the Fourier very low frequencies, and the LF/HF wavelet ratio to the Fourier ratio. The low and high frequencies indices can be also calculated in normalized units, as it is described in the Fourier analysis.

3. Materials

In this section, we present our materials. First, we describe the ECG signal and the synthetic data used to validate the pretreatment and R peak detection phases. Then, we provide an example of using real ECG signals in order to show our approach efficiency (pretreatment, R peak detection and RR interval analysis).

A. ECG Signal

The ECG is a signal that reflects the activity of the heart muscle. It is characterized by five separate waves designated as P, Q, R, S and T (Figure 8). These waves are related to the activity of the atria and ventricles under activation or recovery. The Frequencies for each wave provide variations depending on the heart rate. The change in the beat rate beat is called Arrhythmia. The frequency band of the ECG signals is approximately 50 to 100 Hz for a normal subject.

The RR interval between the R peaks is used for the cardiac arrhythmia diagnosis. A slow rhythm (heart rate <50 beats / mn and the distance RR > 1.2s) corresponds to the bradycardia. The accelerated rhythm (heart rate > 100 beats / mn and the distance RR <0.6s) corresponds to the tachycardia.

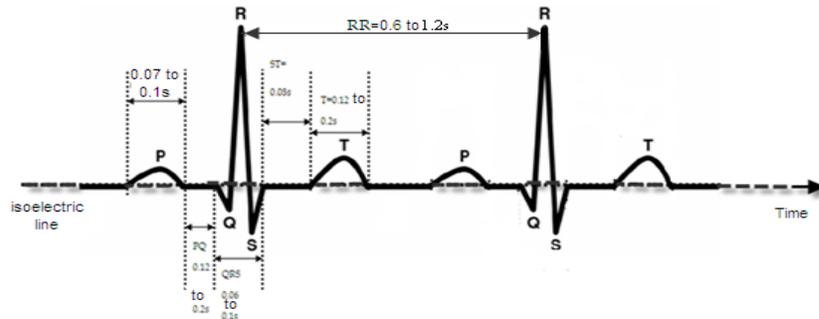


Figure 8. Standard waves of a normal electrocardiogram.

B. Synthetic Data

We use a theoretical signal similar to the real ECG signals (Figure 9). This signal consists only of line segments and coincides with a cardiac cycle. The synthetic ECG signal will be formed by successive translations of the simulated signal portion. We consider a heart rate of about 70 beats per minute, which corresponds to a healthy subject. This heart rate leads to a cycle time $t_c = 0.860s$. The sampling frequency is 256 Hz. Two consecutive samples are thus distant from 0004s. This signal is represented by the following equation:

$$\begin{aligned}
 ECG_{syn}(t) = & (\lambda_{Pt} + \gamma_P)u(t) + [(\lambda_{PQ} - \lambda_P)t + (\gamma_{PQ} - \gamma_P)]u(t - t_P) + [(\lambda_{QR} - \lambda_{PQ})t + \\
 & (\gamma_{QR} - \gamma_{PQ})]u(t - t_Q) + [(\lambda_{RS} - \lambda_{QR})t + (\gamma_{RS} - \gamma_{QR})]u(t - t_R) + [(\lambda_{ST} - \lambda_{RS})t + (\gamma_{ST} - \gamma_{RS})] \\
 & u(t - t_S) + [(\lambda_{TF} - \lambda_{ST})t + (\gamma_{TF} - \gamma_{ST})]u(t - t_T) [-\lambda_{TF}t + (a - \gamma_{TF})]u(t - t_F) - a(u(t - t_c))
 \end{aligned} \tag{13}$$

λ_X are the slopes of the segments, γ_X and a are real constants; $X \in \{P, PQ, QR, RS, ST, TF\}$ such that

$$\begin{cases} \lambda_P = 60.7143 \\ \gamma_P = 0 \end{cases} \quad \begin{cases} \lambda_{PQ} = -41.1111 \\ \gamma_{PQ} = 2.9333 \end{cases} \quad \begin{cases} \lambda_{QR} = 210.5263 \\ \gamma_{QR} = -27.6842 \end{cases}$$

$$\begin{cases} \lambda_{RS} = -155.1724 \\ \gamma_{RS} = 31.1379 \end{cases} \quad \begin{cases} \lambda_{ST} = 27.1739 \\ \gamma_{ST} = -9.0326 \end{cases} \quad \begin{cases} \lambda_{TF} = -29.4117 \\ \gamma_{TF} = 14.0000 \end{cases}$$

$$t_P = 0.028s; t_Q = 0.120s; t_R = 0.160s; t_S = 0.220s; t_T = 0.406s; t_{TF} = 0.476s; t_c = 0.860s$$

We consider $u(t)$ the unit level function.

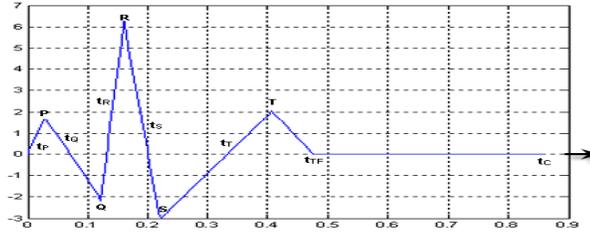


Figure 9. Main model of simulated ECG signal.

To test the robustness of the approach in case of noise, we have chosen to simulate a noisy signal by the addition of Gaussian noise (Figure 10 (b)) such as the probability density function of n-dimensional Gaussian noise is:

$$f(x) = \frac{1}{(2\pi)^n \det K} \exp\left(-\frac{1}{2}(x - \mu)^t K^{-1}(x - \mu)\right) \quad (14)$$

Where x is a length- n vector, K is the n -by- n covariance matrix, μ is the mean value vector, and the superscript t indicates matrix transpose.

C. Real Data

The proposed R peak detection method is evaluated using the MIT-BIH arrhythmia database. It contains 10 minutes of ECG recordings sampled at 256 Hz. The ECG records from this database include signals with acceptable quality, sharp and tall P and T waves, small QRS complex, negative QRS complex, wider QRS complex, baseline drift, muscle noise, sudden changes in QRS morphology, sudden changes in QRS amplitudes, multiform premature ventricular contractions, long pauses and irregular heart rhythms.

4. Results and Discussions

A. Synthetic Data

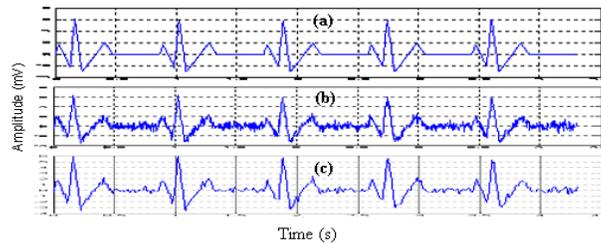


Figure 10. Sample synthetic ECG signal:
(a) initial signal, (b) noisy, (c) filtered by the Daubechies filter.

To purify the noisy synthetic signal, we apply the Db11 high pass filtering in cascade with the Db2 wavelet low pass filtering (Figure 10 (c)).

In Table 1, we present a comparative study by applying the DyWT method on four synthetic signals: initial, noisy, filtered without windowing and filtered with windowing. The number of cardiac cycles of these signals is equal to 600 cycles.

Table 1. Number of R peaks detected of synthetic signals by the DyWT.

original signal without windowing	noisy signal without windowing	Filtered signal without windowing	Filtered signal with windowing
600	510	583	597

According to Table 1, we find that the R peak number is the most raised in the case of an initial signal. This is due to the absence of the noise and to the identical morphology of the R peaks of the synthetic ECG signal. However, in the case of the noisy signal, the detection rate is low. We notice that this rate increases in the case of the filtered signal, more particularly in the case of the filtered signal using the windowing process.

B. Real Data

B.1 Pretreatment of ECG Signal

To use the adopted method in a robust way to effectively detect the R peak and at the demand of the expert, we eliminate the noise associated with the measurement approach (Figure 11).

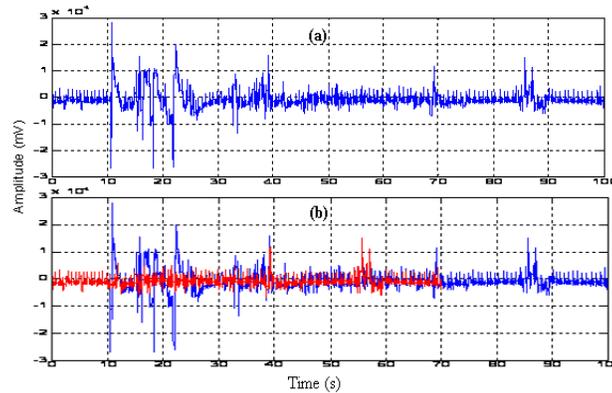


Figure 11. (a) original ECG signal, (b) ECG signal without artifacts (red) superimposed on initial ECG.

In addition, the real data must be filtered to mitigate the undesirable components, such as the P wave, T wave, the drift of the baseline and the noise from the electric grid. As for the synthetic data, the recordings of the ECG signal are filtered by the DWT using the Daubechies wavelet (Figure 12).

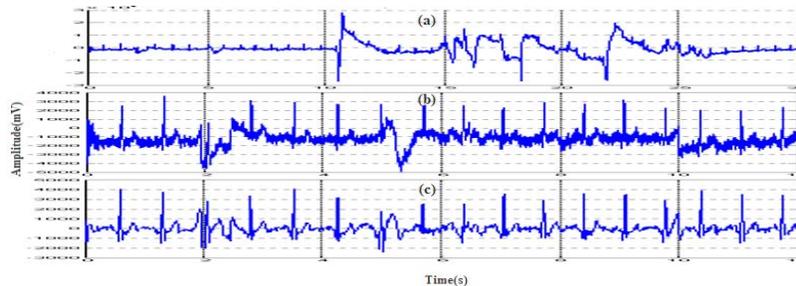


Figure 12. (a) original ECG signal, (b) ECG signal without artifacts, (c) ECG signal filtered.

B.2 Detection of R Peaks

From the detection results, we will evaluate the results basing on two criteria: the first one being the rate of Non Detection (ND) which is the number of labeled R peaks that are not detected. The second being the False detection rate (FD) recorded in the absence of a R peak. The proposed algorithm achieves a significant improvement in the detection of R peaks under time varying QRS complex morphology and different kinds of noise and artifacts. The effectiveness of the proposed method in terms of the number of Non Detection and False Detection is shown in Table 2.

Table 2. Results of the R peaks detection by the proposed algorithm.

Record	The number of present R peaks	R detected	F D	N D	% Error
1	567	567	0	0	0%
2	556	555	0	1	0.18%
3	649	646	1	4	0.77%
4	651	645	0	6	0.92%
5	558	553	1	6	1.25%
6	577	573	0	4	0.69%
7	511	505	0	6	1.17%
8	350	344	0	6	1.33%
9	550	549	0	1	0.18%
10	1236	1236	3	3	0.48%
Total	6105	6073	5	37	0.68%

We note from Table 2 that the results of detection by the DyWT method are very satisfactory, seen the rate of false detections and non detections total is equal to 0.68%. Thus our detection algorithm realize a percentage of R peaks detection equal to 99.32% despite the existence of different types of waves and noises in the recordings which can falsify the detection. Moreover, the DyWT method is very efficient in terms of precision of R peaks location. We make this location by a threshold for the negative minimum and a threshold for the positive maximum. Thus we detect only the real R peaks and not the other waves.

Finally, the overall performance of proposed method is compared with five R peak detectors reported in the literature [2, 5, 7].

Table 3. R peak detection performance comparison with other methods.

Ref.	Method	the number of present R peaks	FD	ND	% Detection rate
[2]	Second discrete derivative stage	109456	884	2112	97.26%
[5]	Neural Network based Adaptive Matched Filtering	4335	35	20	98.73%
[7]	Cubic Spline DWT	22273	14	6	99.57%
[7]	Haar DWT	22273	205	44	99.02%
[7]	Db4 DWT	22273	46	24	99.54%
Our algorithm	Db4 DyWT	6105	5	37	99.32%

B.3 Analysis of RR Intervals

Statistical analysis

In our study, we have L (total length of the recording) = 153600, $T_{\text{samp}} = 1/256^s$

So the beat frequency is equal to:

$$F(\text{beats} / \text{mn}) = \frac{60 \cdot N_{QRS}}{L \cdot T_{\text{samp}}} = 0,1 \cdot N_{QRS} \quad (15)$$

From the proposed R peaks detection algorithm, we calculate the standard deviation which is an indicator of the overall variability in the heart rate. The automatic extraction result of this parameter is given in Table 4.

Table 4. Frequency recordings deduced by proposed algorithm application.

Record	Frequency (rpm)	Standard Deviation
1	56.7	9.21
2	55.5	4.9
3	64.6	6.3
4	64.5	5.56
5	55.3	2.89
6	57.3	4.27
7	50.5	3.79
8	34.4	12.33
9	54.9	3.993
10	123.6	13.21

Fourier analysis

We study the Power Spectral Density (PSD) of 10 minutes RR intervals of three subjects: the first is healthy (record 1), the second suffers from tachycardia (record 10) and the third suffers from Bradycardia (record 8). We calculate frequency indices of HRV which are presented in Table 5.

The results depicted in Table 5 demonstrate that the PSD obtained in all frequency bands (VLF, LF and HF) decreases with the increase in heart rate. These results indicate that HRV measurement is affected by the slowness or the acceleration of the heartbeat. Moreover, the evolution of the LF/ HF, LF/LF+HF and HF/LF+HF reports is different at the three subjects. At a tachycardia subject, the LF percentage is greater than the HF percentage which indicates that the sympathetic nerves are more active and this situation causes the heart

Table 5. Indices of HRV Fourier analysis.

Indices	Healthy subject	Tachycardia subject	Bradycardia subject
VLF (ms ²)	353.840	82.848	3315.3
LF (ms ²)	445.3	392.776	460
HF (ms ²)	434.4	208.201	553.776
Ratio (LF/HF)	1.025	1.886	0.83
Total power (ms ²)	1233.54	683.825	4329.076
LFnu	50.619	65.356	45.374
HFnu	49.380	34.643	54.625

rate of the subject to be quicker than the ordinary situation. However, at a bradycardia subject, we notice that the ANS behavior is characterized by an increase of the concentrated power at the HF band level with regard to the LF band. The pursuit of these changes is clear in the LF and HF powers of Fourier analysis in each subband measured in normalized units. These changes generate the parasympathetic stimulation and consequently slowing the heart rate. At

the healthy subject, the LF/HF ratio is approximately equal to 1 which reflects autonomic nervous system equilibrium.

Wavelet analysis

We are also interested in studying the temporal evolution of the frequency organization. It is the field of wavelet method application. We are interested in the HRV study of 10 minutes RR intervals of the same three subjects used in the Fourier analysis. Also, we calculate the time-frequency indices of HRV which are presented in Table 6. The results depicted in this Table confirm the results obtained in the HRV Fourier analysis.

Table 6. Indices of HRV wavelet analysis.

Indices	Healthy subject	tachycardia subject	bradycardia subject
VLF (s^2)	4.7138	1.995	38.6
LF (s^2)	4.8725	3.2142	4.8944
HF (s^2)	4.8588	2.2112	6.6039
Ratio (LF/HF)	1.002	1.453	0.741
Total power (s^2)	14.4451	7.4204	50.0983
LFnu	50.07	59.243	42.566
HFnu	49.93	40.756	57.433

5. Conclusion

The spectral analysis is currently highly demanded by clinicians in order to obtain clinical markers for certain diseases. The study of the Heart Rate Variability appears to be a useful indicator for the diagnosis, prognosis and treatment of certain diseases. In this context, the objective of this work is to study the HRV in healthy and sick persons, using the FFT in the frequency domain and the wavelet transform in the time-frequency domain.

Starting with the filtering algorithms of the ECG, we performed a low frequency filter to eliminate deviations from the baseline by a filter based on the coefficients of the DWT and zeroing of the approximation coefficients which are responsible for the movements of the baseline. Then we propose filtering the noise of rapid changes in the ECG signal by thresholding the coefficients of the detail. To continue this work, we develop an algorithm for the localization of the R peak of the QRS complex by applying in ECG signal a method that is based on DyWT. In the case of QRS complex, this method gives a defining couple negative minimum-positive maximum, and an interval in which we have investigated the R peaks. The main advantages of this method are its robust noise performance, its flexibility in analyzing non-stationary ECG data and less time consuming for long time ECG signal.

The obtained results show that the R peaks can be estimated with a good accuracy. From the R peaks detection algorithm, we deduce the heartbeat frequencies and the standard deviation of recordings. Finally, we study the HRV in healthy and diseased subjects in the frequency and time-frequency domains.

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