New Method of R-Wave Detection by Continuous Wavelet Transform

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Abstract

In this paper we have employed a new method of R-waves detection in electrocardiogram (ECG) signals. This method is based on the application of the discretised Continuous Wavelet Transform (CWT) used for the Bionic Wavelet Transform (BWT). The mother wavelet associated to this transform is the Morlet wavelet. For evaluating the proposed method, we have compared it to others methods that are based on Wavelet Transform (WT). In this evaluation, the used ECG signals are taken from MIT-BIH database. The obtained results show that the proposed method outperforms some conventional techniques used in our evaluation.

Keywords: Continuous Wavelet Transform, Electrocardiogram, Hard Thresholding, R-wave Detection.

1. INTRODUCTION

The electric currents in the heart have been measured and recorded for more than a hundred years, but the term electrocardiogram (ECG) was introduced by Willem Einthoven in 1893 at a meeting of the Dutch Medical Society. The electrocardiogram is considered to be the backbone of cardiology, and can be recorded fairly easily with surface electrodes on the surface of the limbs or chest. The ECG records the electrical activity, this typical tracing consists of a series of repetitive waves namely P, Q, R, S and T. The P wave represents left and right atrial depolarization, ventricular contractions (both right and left) show as a series of 3 waves, Q-R-S know as the QRS complex, the last common wave in an ECG is the T wave, this reflects the period of ventricular repolarization. A cardiologist can look at a patient's electrocardiogram and determine the presence of disturbances in the intervals, amplitudes and areas of these waves. QRS complex is the most prominent feature in electrocardiogram because of its specific shape; therefore it is taken as a reference in ECG feature extraction. R wave detectors are very useful tools in analyzing ECG features thus form the basis of ECG feature extraction [1]. The development of accurate and quick methods for automatic ECG feature extraction is of major importance, especially for the analysis of long recordings (Holters and ambulatory systems). In fact, beat detection is necessary to determine the heart rate, and several related arrhythmias such as Tachycardia, Bradycardia and Heart Rate Variation [2]. All methods used by scientists are to help cardiologists to gain time to interpret results and improve the diagnostic.

In this paper, we proposed a technique using discretized continuous wavelet transform (CWT), 'Morlet' mother wavelet has been selected for detection of R-wave. The method described is robust, does not require any pre-processing stage, simple to implement and the selection of detail signal C4 has been justified. Finally, the ECG signals used in the experiments are obtained from MIT-BIH database [3].

2. MATERIAL

2.1 Continuous Wavelet Transform (CWT)

Morlet first introduced the idea of wavelets as a family of function constructed from translations and wavelets of a single function called the 'mother wavelet'. The wavelet analysis has been introduced as a windowing technique with variable-sized regions. Wavelet decomposition introduces the notion of scale as an alternative to frequency and maps a signal into time-scale plan. The wavelet analysis is the decomposition of a signal into sine waves of different frequencies [4]. Mathematically, the continuous wavelet transform of a function $x(t)$ is defined as the integral transform of $x(t)$ with a family of wavelet functions, $\Psi_{a,b}(t)$:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \cdot \Psi\left(\frac{t-b}{a}\right) dt,\ a \in IR_{+}^{*}, b \in IR \tag{1}$$

The function $\Psi(t)$ is commonly called the mother wavelet and the family of function $\Psi_{a,b}(t)$ is called daughter wavelets. The daughter wavelets are derived from scaling and shifting the mother wavelet. The scale factor a represents the scaling of the function $\Psi(t)$, and the shift factor b represents the temporal translation of the function. It is important to know that determination of CWT scale parameter and mother wavelets are very significant in ECG feature extraction [4].

In this work, we have used the discretized CWT employing the Morlet wavelet. This discretized CWT is used for the Bionic Wavelet Transform (BWT) introduced by Yao et al [5].

2.2 Wavelet Selection

The selection of the analyzing function in wavelet transforms, which is called the mother wavelet, has a significant effect on the result of analysis and should be selected carefully based on the nature of the signal [6]. But there is no universal method suggested to select a practical wavelet. They are several wavelet families like Biorthogonal, Coiflets, Daubechies, Morlet, Symlets etc. In this study, 'Morlet' mother wavelet has been selected for feature extraction. The analysis shows that extracted features from ECG signal by using the Morlet mother wavelet would be simple to compute, easy to understand, and the results are very good. Figure 1 shows the real and imaginary parts of the complex Morlet mother wavelet.

2.3 Data Base

The data available from MIT-BIH Arrhythmia Database [3] is the standard used by many researchers. The MIT-BIH database contains many data sets of electrocardiogram signals, mostly abnormal or unhealthy electrocardiograms, but it also contains normal electrocardiograms that can be used as a reference base [7]. This contains two lead ECG signals of 48 patients. The selected Arrhythmias are Premature Atrial Beat (PAB), Premature Ventricular Beat (PVB), Right Bundle Branch Block (RBBB), and Left Bundle Branch Block (LBBB).

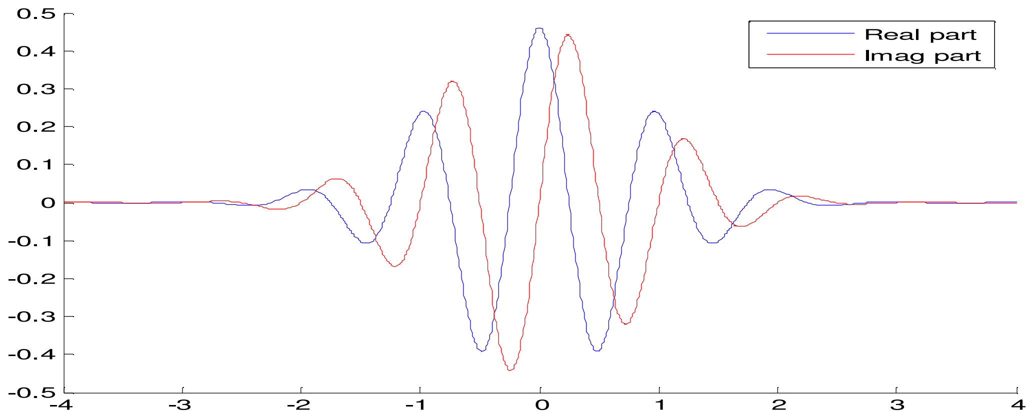


FIGURE 1: The Morlet Wavelet (its real part and imaginary part).

3. MATERIAL
The ECG signals taken from MIT-BIH arrhythmia database are converted in to Matlab format (.mat files). The ECG signal is sampled at 360 Hz with a resolution of 11 bits. In this section, we have developed and evaluated a robust method R-Wave detection based on Continuous Wavelet Transform. This technique is summarized by the following steps:

Step1: we decompose the ECG signal into 8 scales by using the modified discretized continuous wavelet transform MMycwt which is used by BWT.
Step2: we chose the best wavelet coefficient to perform the detection of R-wave: this selection is based on the research work of Awadhesh Pachauri et al [1].
Step3: we apply hard thresholding to that coefficient by using the appropriate threshold.
Step4: we detect R-waves by using the step3: the positions of the R-waves are those having amplitudes that are greater than the value of the selected threshold.

The Figure 2 gives in details the different steps of the proposed technique and they will be detailed in the next paragraph.

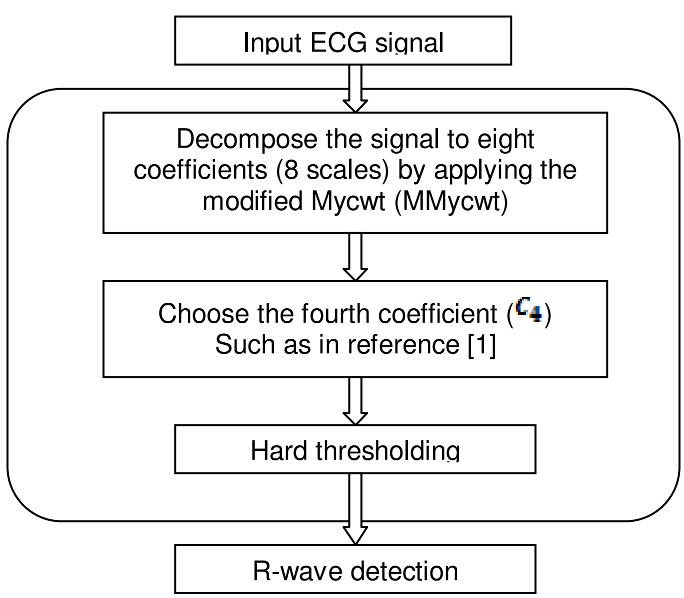


FIGURE 2: The different steps of the proposed technique of the R-waves detection.

3.1 MMycwt

For an ECG signal, the most important feature is the frequency range in which its main components occur [8]. Despite the existence of some other components like VLPs, we are interested in this paper in P, Q, R, S and T waves such as in the reference [8]. In references [9, 10], the value of (the initial center frequency of the mother wavelet) is equal to 15165.4Hz. As the scale increases, the center frequency goes smaller and smaller in the following way:

$$f_m = f_0/q^m, q > 1, m = 1, 2, \ldots \quad (2)$$

We don't need such high frequency for ECG signals. Omid et al [8] have optimized the value of by running the program for different values of and then minimizing the gradient of error variance by comparing the results-numerically and morphologically with each other. It has been found that if belongs to the range of 360 to 500Hz there would be no much distortion on the analyzed ECG signals [8]. In their work, Omid et al [8] have chosen 400Hz as the value of f_0. Hence, in our work, we have chosen $f_0 = 250\text{Hz}$ in order to obtain the MMycwt. In this paper, we have chosen the value 1.1623 as that of q such as in the reference [9, 10].

Every ECG signals under test are decomposed up to 8 levels. The maximum number of decomposition level depends upon total number of samples present in the signal.

$$n = 2^N \quad (3)$$

where N is the total number of levels of decomposition and n is the total number of samples in the ECG signal.

3.3. Selection of Detail Coefficient (C_4)

According to the reference [1], it was shown by simulation that the wavelet coefficient in level four, owns the highest coefficient of cross correlation with the original signal therefore we have chosen in this work, this coefficient to detect R-peaks.

3.4. Thresholding

After applying the CWT to the input ECG signal, the fourth wavelet coefficient we apply the hard thresholding to fourth wavelet coefficient, C_4 and the threshold is selected to be:

$$Thr = \alpha \times \max(C_4) \quad (4)$$

$$\text{If } C_4(i) \leq Thr$$
$$C_4(i) = 0$$

where α is a positive parameter belonging to the range of 0.3 to 0.9.

4. RESULTS AND VALIDATION

The algorithm has been tested on MIT-BIH arrhythmia databases in which every recording is of 30 minutes duration, 10 records were tested for R peaks to evaluate our algorithm. In our evaluation of the proposed technique, we have calculated the Sensitivity, the Positive predictivity and the Error which:

- Sensitivity: $$S_e = \frac{TP}{TP+FN} \quad (5)$$

- Positive productivity: $$P^+ = \frac{TP}{TP+FP} \quad (6)$$

• Error : $$\%error = \frac{FP+FN}{Total\ beats} \tag{7}$$

Table1 shows that our method achieves very good detection performance. This algorithm attains sensitivity of 99.96% and a positive predictivity of 99.84% without the need to apply any pretreatment to the original signal.

Tape (N°)	Total N° beats	FP beats	FN beats	P^+ (%)	S_e (%)
100	2273	0	0	100	100
101	1865	0	2	100	99.89
102	2187	13	4	99.40	99.81
103	2084	0	0	100	100
104	2230	21	0	99.06	100
105	2572	0	0	100	100
106	2027	0	0	100	100
107	2137	0	1	100	99.95
111	2124	0	0	100	100
112	2539	0	0	100	100

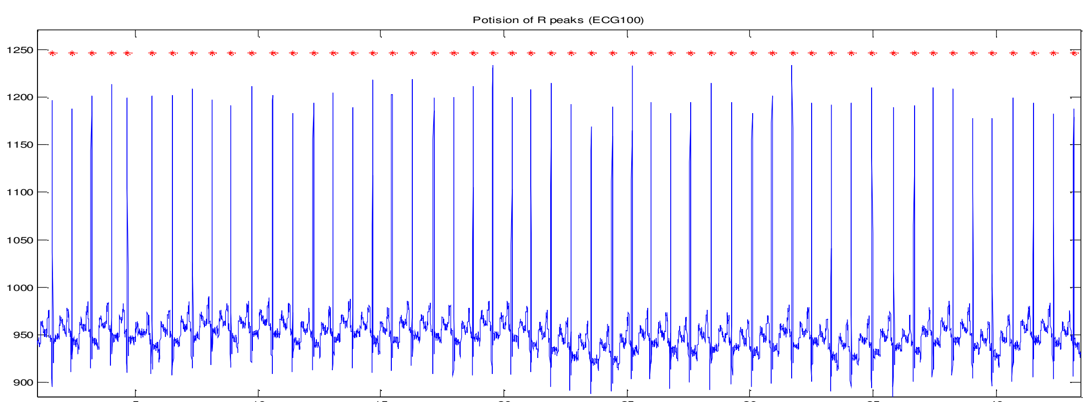
TABLE 1: Performance of the proposed classification model for test data.

Table2 shows that the proposed method outperforms some conventional techniques used in our evaluation such as the techniques of Arzeno et al. [11], Mahmoodabadi et al. [2] and Hubin and Jiankiang [12]. The technique of Rym Besrour et al. [13] gives the best result in term of %error and the proposed technique comes in the second place. The latter gives the best result in term of Se % and the technique of Jasko [14] is the best in term of P+ %.

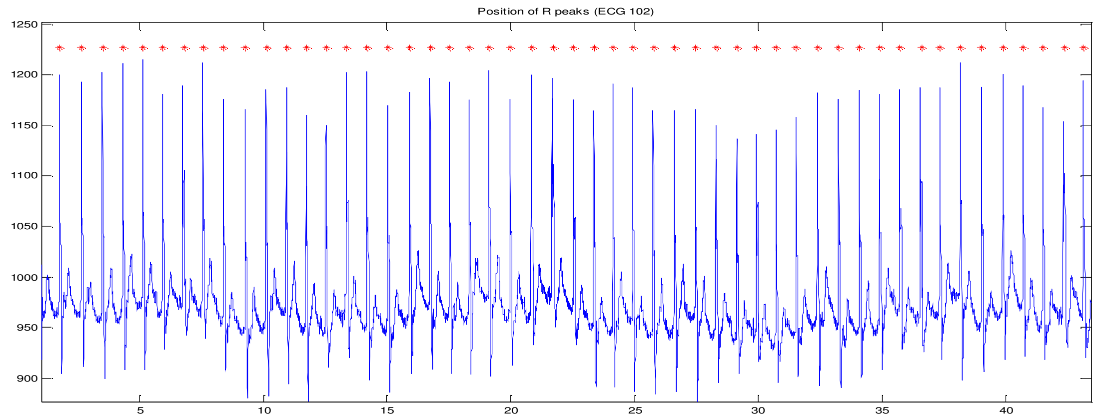
QRS detector	S_e %	P^+ %	% error
Arzeno et al.[11]	99.29 99.57 98.07	99.24 99.59 99.18	1.47 0.84 2.75
Huabin and Jiankiang [12]	99.68	99.59	0.73
Josko [14]	99.86	99.91	0.23
Mahmoodabadi et al.[2]	99.18	98	2.82
Rym Besrour et al [13]	99.92	99.88	0.19
Martinez et al. [15]	99.80	99.86	0.34
This work	**99.96**	**99.84**	**0.2**

TABLE 2: R wave's detection results on MIT-BIH database.

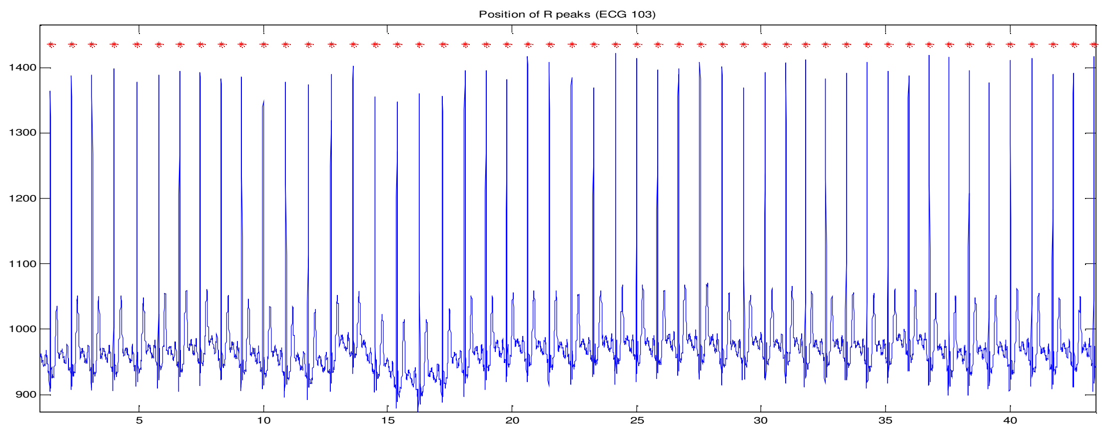
The positions of the R peaks are detected and marked by the symbol '*' on the original signal. Figure 3 illustrates some examples of R-wave detection using the proposed technique.



(a)



(b)



(c)

FIGURE 3: Original ECG signals and positions of R peaks (a) 100 (b) 102 (c) 103.

Those examples show the efficiency of the proposed R-wave detection technique. When we especially compare our proposed technique to the technique of Awadhesh Pachauri et al [1], we see clearly that the proposed technique outperforms the second technique. The proposed technique gives 99.96% as a result of $\mathbf{S_e}$ computation and about 99.84% for $\mathbf{P^+}$ whereas the achieved overall accuracy of detection using db6 and sym11 are 96.65% and 84.37% respectively and this for the second technique of Awadhesh Pachauri et al[1]. Moreover, when we use the thechnique of Awadhesh Pachauri et al [1], we can see clearly in figure 4, that there is a great difference between some detected R-peak positions and the real positions of those peaks. This shifting in R-peaks positions is particularly absent when we use our proposed technique.

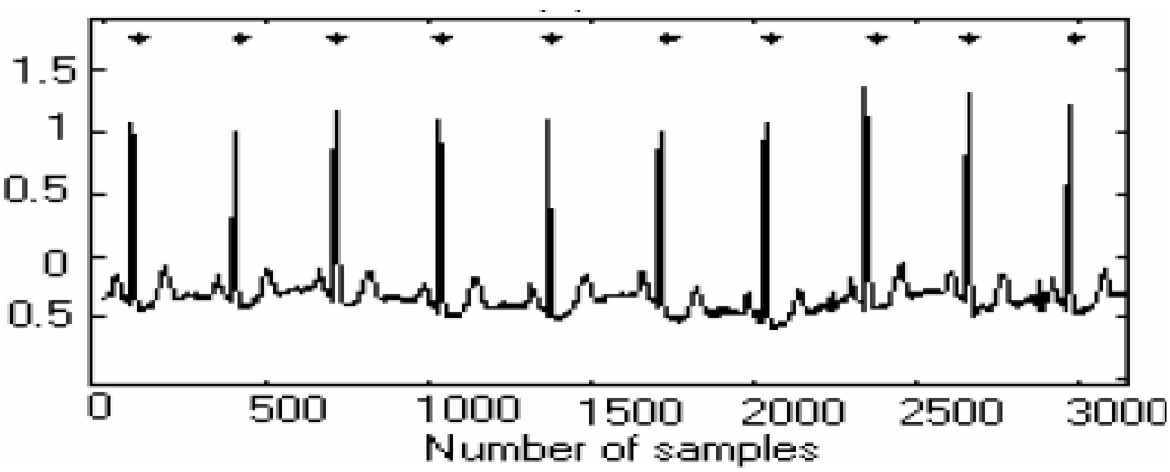


FIGURE 4: Shifting in R-peak positions marked by the technique of Awadhesh Pachauri et al[1].

The performance of the proposed technique can be seen as a result of the use of the discretised continuous wavelet transform which is modified (MMycwt) according to the characteristics of the ECG signal. The latter has less dynamics than a speech signal for example. Therefore it is more suitable to use a discrete transform than a continuous transform. Moreover the length of each coefficient obtained from the MMycwt application to an ECG signal, is the same length of that signal so this fact permits to facilitate the detection of the R-wave positions.

5. CONCLUSION

In this paper we have presented a new method for R wave detection using discretised continuous wavelet transform used by the bionic wavelet transform (BWT). This transform was modified according the ECG signal characteristics in order to obtain the MMycwt. The mother wavelet associated to this transform is the Morlet wavelet. We have decomposed the ECG signal into 8 scales and we have chosen the fourth coefficient in order to detect the R-peaks. This detection is performed by applying a hard thresholding to the fourth coefficient obtained from the application of the MMycwt to the ECG signal. The algorithm has been validated using MIT-BIH standard database and is compared to some others techniques. The obtained results from S_e and P^+ computation, show that the proposed technique outperforms the others techniques used in our evaluation.

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