Detection of QRS Complexes in the ECG Signal using Multiresolution Wavelet and Thresholding Method

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Abstract

The electrocardiogram (ECG) is a diagnostic tool that measures and records the electrical activity of the heart in exquisite detail. Interpretation of these details allows diagnosis of a wide range of heart conditions.

Automatic extraction of time plane features is important for cardiac disease diagnosis. This paper presents a multi-resolution wavelet transform based system for detection and evaluation of QRS complex. In first step of this paper we use the selective confident method to find the QRS complex, at next step we use a threshold method to find the QRS complex and finally we apply the composition of first step algorithm and thresholding method which shows robust ability of finding QRS compared to other methods. Achieved overall accuracy of QRS detection for only d_4 *scale without threshold is 84.48%, the composition of* d_3, d_4, d_5 *without threshold 93.23%, only* d_4 *with threshold 90%, and* d_3, d_4, d_5 *with threshold 98.2%.*

1. Introduction

The electrocardiogram is an important tool for providing information about functional status of the heart. Analysis of ECG is of great importance in the detection of cardiac diseases which are the main cause of mortality in many countries.

The Q, R and S wave of ECG signal occur in rapid succession, do not all appear in all leads and reflect a single event so are thus normally considered as a whole complex. A Q wave is any downward deflection after the P-wave. An R-wave is an upward deflection and the S wave is any downward deflection after the R-wave.

The QRS complex of the electrocardiographic signal has the normal duration from 0.06s to 0.1s and provides information about the heart rate, the conduction velocity, the condition of tissues within the heart and various abnormalities. Its shape, duration and time of occurrence provide valuable information about the current state of the heart. Because of its specific shape, the QRS complex serves as an entry point for almost all automated ECG analysis algorithms and detection of the QRS complex is the most important task in automatic ECG signal analysis [1].

Ventricles contain more muscle mass than the atria, therefore the QRS complex is considerably larger than the P wave. The QRS complex is often used to determine the axis of the electrocardiogram .The atrial repolarization wave, which resembles an inverse P wave, is buried inside the QRS wave. The atrial repolarization wave is obscured by the QRS because it is far smaller in magnitude. The duration, amplitude, and morphology of the QRS complex is useful in diagnosing cardiac arrhythmias, conduction abnormalities, ventricular hypertrophy, myocardial infarction, electrolyte derangements, and other disease states.

The QRS detection is not a simple task, due to the varying morphologies of normal and abnormal complexes and because the ECG signal experiences different types of disturbances with complex origin [2].

There are several methods for detection of significant points of ECG. Some of these methods are, low pass differentiation (LPD), Multichannel ART-based neural network (MART), wavelet transform (WT), and etc.

In signal processing, there are a number of different functions that can perform on the signal in order to translate it into different forms that are more suitable for different applications. The most popular function is the Fourier transform that converts a signal from time versus amplitude to frequency versus amplitude. This transform is useful for many applications, but it is not based in time. To combat this problem, mathematicians came up with the short term Fourier transform which can convert a signal to frequency versus time. Unfortunately, this transform also has its shortcomings mostly that it cannot get decent resolutions for both high and low frequencies at the same time.

So to converted and manipulated the signal while keeping resolution across the entire signal and still being based in time, wavelets come into play. Wavelets are finite windows through which the signal can be viewed. In order to move the window about the length of the signal, the wavelets can be translated about time in addition to being compressed and widened.

Using DWT in feature extraction may lead to an optimal frequency resolution in all frequency ranges as it has a varying window size, broad at lower frequencies, and narrow at higher frequencies. The DWT characterization will deliver the stable features to the morphology variations of the ECG waveforms [3].

This Research presents a multi-resolution wavelet transform based system for detection and evaluation of QRS complex. In first step of this paper we use the represented algorithm in [2], and fined the QRS complex, at next step we use a threshold method to find the QRS complex and finally we apply the composition of first step algorithm and thresholding method which shows robust ability of finding QRS in compared to other methods. The performance of the system is validated using original 12 lead ECG recording collected from the Physionet PTB diagnostic database [8].

2. Discrete wavelet transform (DWT)

A wavelet is a waveform of effectively limited duration that has an average value of zero. Similar to Fourier series analysis, where sinusoids are chosen as the basis function, wavelet analysis is also based on a decomposition of a signal using an orthonormal (typically, although not necessarily) family of basic functions. Unlike a sine wave, a wavelet has its energy concentrated in time. Sinusoids are useful in analyzing periodic and time-invariant phenomena, while wavelets are well suited for the analysis of transient, time-varying signals, thus well suited for ECG signals. Basically wavelet transform is the convolution operation of the subject signal $f(t)$ and the wavelet function $\psi(t)$. The discrete wavelet transform is expressed as,

$$X_{j,k} = \int_{-\infty}^{\infty} f(t)\psi_{j,k}(t)dt \tag{1}$$

The approximation coefficient of the signal $f(t)$ is represented as,

$$A_{j,k} = \int_{-\infty}^{\infty} f(t)\phi_{j,k}(t)dt \tag{2}$$

Where $\phi(t)$ is scaling function, j and k are scale and location respectively. For a range of scale n, the original signal $f(t)$ under discrete wavelet transform can be represented as,

$$f(t) = f_n(t) + \sum_{j=1}^{n} d_j(t) \tag{3}$$

Where $f_n(t)$ is mean signal approximation and is given by,

$$f_n(t) = A_{n,k}\phi_{n,k}(t) \tag{4}$$

and $d_j(t)$ is detail signal approximation in scale j.

Thus given an approximation of a signal using translations of a mother wavelet up to some chosen scale, a better approximation can be achieved by using expansion signals with half the width and half as wide translation steps. The wavelet transform as such decomposes a signal into two sub signals – detail signal and approximation signal. Detail signal contains the upper half of the frequency components and approximation signal contains the lower half.

The decomposition can be further repeated on the approximation signal in order to g t the second detail and approximation signal. Thus in discrete wavelet domain, multi-resolution analysis can be performed.

2.1. Wavelet selection

The large number of known wavelet families and functions provides a rich space in which to search for a wavelet which will very efficiently represent a signal of interest in a large variety of applications. Wavelet families include Biorthogonal, Coiflet, Harr, Symmlet, Daubechies wavelets, etc. There is no absolute way to choose a certain wavelet. The choice of the wavelet function depends on the application. To obtain the wavelet analysis, we used the Matlab program, which contains a very good wavelet toolbox. First the considered ECG signal was decomposed using db6 wavelet of the order of 1-8 has been evaluated.

3. Detection of peaks

In order to detect the peaks, specific details of the signal were selected. The method developed by Li et al [4] involves preprocessing of initial QRS beats to select modulus maxima greater than threshold and post processing to remove the unrelated noisy peaks appearing as R-waves. The method uses four thresholds for the detection of modulus maxima at four different scales. Mahmood abadi[5] suggest the selection of details d3-d5 for R-Wave detection, whereas S.C.Saxena et al [6] employs detail signal d4 for detection of QRS peak. Awadhesh Pachauri, and Manabendra Bhuyan[7] represent a method without requirement of preprocessing and the selection of detail signal d4 has been justified by energy, frequency and correlation analysis. Furthermore, they calculate total number of R waves using hard thresholding.

In this paper we use we apply the composition of use the selective confident method [2] and thresholding method which shows robust ability of finding QRS in compared to other methods.

3.1. R peak detection

R peak is the largest amplitude point which is greater than threshold points are located in the wave.

Small scales (1-4), represent the high frequency components and large scales represent the low frequency components of sample ECG signal. Eighth level reconstruction coefficients represent high frequency contents of the ECG waveform which in most of the cases appear to be high frequency noises. It is clear that most energy of the QRS complex is concentrated at decomposition level 3, 4 and 5. Thus, d3, d4 and d5 coefficients are identified for the detection of QRS complex.

$$e_1 = d_3 + d_4 + d_5 \quad (5)$$

Although the QRS region is properly captured but it is difficult to identify R peak due to its oscillatory nature. So, a function e_2 is defined as [2],

$$e_2 = \frac{d_4(d_3 + d_5)}{2^n} \quad (6)$$

Where n is the level of decomposition. Then the modulus of $e_1 \times e_2$ is taken. The accuracy of the entire feature extraction work mainly depends upon the identification accuracy of R peak.

3.2. Thresholding method

The selected detail coefficient d_4 is used to perform the detection of R-wave. For this purpose a practical lower limit is applied to remove unrelated peaks appearing due to noise.

There are several thresholding methods known. Here we apply hard thresholding in which the samples below a predetermined threshold are set to zero. The threshold is selected as 15% of maximum value of d_4 and applied as follows [4]:

$$threshold = \%15 \times \max(d_4)$$
$$if\,(d_4(i)) = threshold$$
$$(d_4(i)) = 0$$

In some researches the detail coefficient d_4 has been chosen to detect R wave based on Energy, frequency and correlation Analysis [4]. In this research we compared the results of R detection based on only d_4, and composition of d_3, d_4, d_5, also we apply both of these cases with and without using threshold method. The results are shown in Figures 1, 2 and 3 respectively.

3.3. Q and S detection

A Q and S peak occurs about the R peak with in 0.1second. Calculating the distance from zero point or close zero left side of R peak within the threshold limit denotes Q peak.

Once the R peak is detected, the Q and S points are to be identified to detect the complete QRS complex. Generally the Q and S waves have high frequency and low amplitude and their energies are mainly at small scale. So, decomposition coefficients from d2 to d5 are used. Q and S points are the points of inflexion in either side of the R peak. So the first zero slope points on either side of the R peak will represent the Q and S point. Figure 1 shows the detected QRS complex. First two zero slope points on either side of R peak (as detected earlier) are identified as Q and S points respectively.

3.4. QRS detection with baseline drift

In order to evaluate the represented algorithm of finding QRS complex and R wave, we apply this algorithm on an ECG signal with baseline drift. Since there was not an available ECG signal with baseline drift, we use a manipulate signal which made from an ECG signal added to a random sinuous and cosines wave. Then the algorithm was applied on manipulate signal. The result of QRS and R wave detection are shown in Figure 3.

4. Results

In the present work, physionet PTB diagnostic database is used to detect the QRS complex. As discussed in the previous section, simulation and testing has been carried out, the results of which are presented in Figures 1-4. For validation of the algorithm, 50 databases were checked. Achieved overall accuracy of QRS detection for only d_4 scale without threshold is 84.48%, the composition of d_3, d_4, d_5 without threshold 93.23%, only d_4 with threshold 90%, and d_3, d_4, d_5 with threshold 98.2%.

5. Conclusion

In this paper, an algorithm based on Wavelet Transform is presented for the detection of QRS complex of ECG signal. Wavelet Decomposition of ECG wave up to level 8 using orthogonal Daubechis 6 wavelet generates 8 scales of detail coefficients. The multi-resolution wavelet transforms based system with different wavelet scales used to find the QRS complex, and finally the composition of selective confident and thresholding method shows robust ability of finding QRS compared to

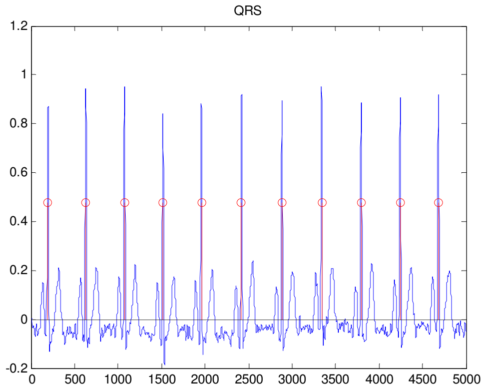

Figure 1. QRS detection on ECG signal.

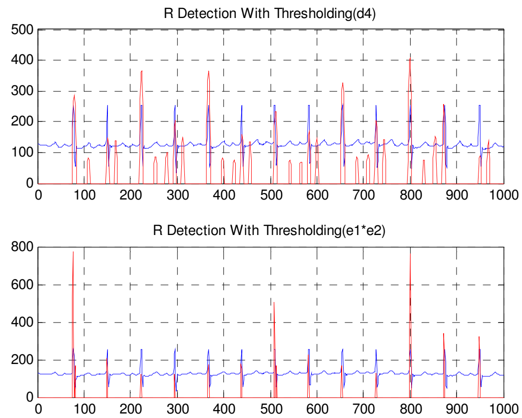

Figure 3. Comparison of R detection with threshold based on d_3, d_4, d_5 and d_4.

other methods. From the result, it can be seen that this method is having a comparatively high sensitivity, so it can be used as a useful and robust tool for automatic and on line disease classification and biometric recognition. Since the application of wavelet transformation in electro cardiology is relatively new field of research, many methodological aspects (Choice of the mother wavelet, values of the scale parameters) of the wavelet technique will require further investigations in order to improve the clinical usefulness of this novel signal processing technique. Simultaneously diagnostic and prognostic significance of wavelet techniques in various fields of electro cardiology needs to be established in large clinical studies. But some of the ECG waveform may show very erratic nature due to electrode contact noise or some complicated cardiac abnormalities. The algorithm is not tested with them because of lack of availability of that special kind of database.

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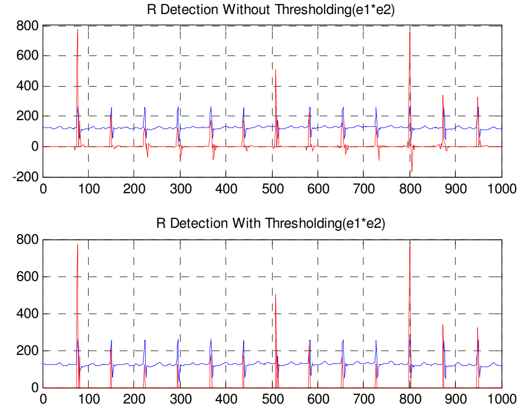

Figure 2. R detection with and without threshold based on d_3, d_4, d_5.

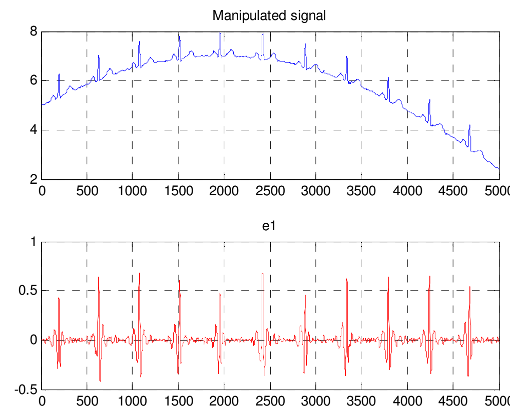

Figure 4. QRS detected in ECG signal with baseline drift.

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