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De-noising of ECG Signal and QRS Detection using Hilbert Transform and Adaptive Thresholding

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Abstract

Electrocardiogram (ECG) is a primary diagnostic tool for cardiac disorders. During acquisition of ECG signals different noises like instrument noise, muscle noise, motion artifacts and baseline wander are frequently mixed with signals in real-time situation. The segmentation and detection of R peaks in the ECG is the initial steps in HRV analysis. In this paper, we employ the discrete wavelet transform to remove noise components of the time - frequency domain in order to enhance the ECG signal and the Hilbert transform with the adaptive thresholding technique used to explore an optimal combination to detect R-peaks more accurately. The proposed method is evaluated on ECG signals from MIT database. The experimental results of present method show better signal to noise ratio (SNR) with lower mean square error (MSE). To evaluate the quality of physiological information preserved in the enhanced ECG signal, the R-peak detection was also tested. The performance of the proposed method is found to be better in detecting R-peaks having sensitivity of 99.71% and the positive predictability of 99.72% respectively with less detection error rate of 0.52%.

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Keywords: Electrocardiogram, noise, adaptive thresholding, Hilbert transform, R-peaks, accuracy;

1. Introduction

The electrocardiogram (ECG) signal is the recording of the electrical activity of the heart which provides the clinical information about the condition of heart [1]. The analysis of ECG signal plays a significant role in the diagnosis of heart diseases. Detection of ECG arrhythmias is necessary for the treatment of patients for diagnosing the heart disease at the early stage. The artifact like power-line noise, instrumentation noise and motion artifact (MA), affects the originality of the signals [2]. Therefore, to enhance the conditions of ECG signals, the digital
filters and adaptive filters with appropriate filter parameters are often used to remove noise. The signal is characterized by electrical activity during a cardiac cycle named as QRS complexes, P and T waves [3]. Detection of QRS complex and R-peak is one of the most important parts of the ECG signal analysis. The cardiac arrhythmias are detected by choosing the accurate QRS complex. The detection of the QRS complex and Peaks in the ECG wave is a difficult task due to time-varying morphology, physiological variations of the patient and noise. Therefore the development an efficient feature extraction algorithm is of great importance in the analysis of ECG signals.

Till now, differentiation methods and digital filters are used for detection of QRS complex or the R-point in the ECG signal processing [4-7]. The Pan-Tompkins method is commonly used for R-point detection in the ECG due to its computational simplicity [8]. Techniques based on neural networks (NNs), adaptive filtering, wavelet transform and empirical mode decomposition (EMD) have been extensively used to de-noise the ECG signals [9-11]. The wavelet transforms and EMD based methods are found to be more effective in de-noising the non-stationary ECG signals. The wavelet transform has been used in ECG characterization and QRS detection, but is imitated by fixed duration windowing techniques in detecting time-varying transients for which an adaptive technique is needed [12]. In an EMD-wavelet based method, the signal is analyzed by adoptive thresholding to eliminate the high frequency noise and the QRS information [13]. Different methods have been used to improve the detection accuracy of QRS complex, including the use of the Hilbert transform. The Hilbert transform has been able to distinguish between dominant peaks in the signal; therefore it improves the results to detect R-peaks [14-18]. It was first described by Bolton and Westphal for ECG analysis. This method examines the concept of pre-envelope and envelope of a real ECG waveform for optimum detection of the R-peak. With an innovative approach based on first-derivative, Hilbert and Wavelet transforms with adaptive thresholding was found to be detected more accurately the morphology of QRS complex [19]. In a very recent work, the Hilbert transform was used to detect R-peak by determining the location of the onset and systolic peak of the arterial pulse wave. The results provide an accurate onset and systolic peak detection and can be used in the measurement of pulse transit time, pulse wave velocity and pulse rate variability [20].

This paper describes an application of Hilbert transform with adaptive thresholding for QRS complex and R-peak detection by using recorded signals from the MIT-BIH database. The noisy ECG signal is filtered with a windowing operation using wavelet transform to preserve the information of QRS complex. The implemented results are evaluated both quantitatively and qualitatively for testing the performance of the algorithms. The simulation result shows that the proposed method de-noises the ECG signal effectively at different levels of SNR in comparison to some of the state-of-the-art methods.

2. Wavelet Transform

The wavelet transform decomposes the non-stationary signal into a number of scales having different frequency component and analyses each scale with a certain resolution for getting accurate features of the signal. The sum of overall time of the signal multiplied by a scaled and shifted version of the wavelet function $\Psi$ is given as:

$$H(a,b) = \int_{-\infty}^{\infty} x(t) \Psi_{a,b}(t) dt$$

where, $x(t)$ is the original signal, $^*$ denotes the complex conjugation, $\Psi_{a,b}(t)$ is the window function of the mother wavelet and $\Psi^*\left(\frac{t-b}{a}\right)$ is its shifted & scaled version. The Discrete Wavelet Transform (DWT) is chosen mostly in practical application for accurate reconstruction of the signal due to its low computational complexity over FFT. Hence DWT is defined mathematically as:

$$H(a,b) = p(j,l) = \sum_{n \in \mathbb{Z}} x(n) \Psi_{j,l}(n)$$

where, $a=2^j$ and $b=2^j l$ ; $\Psi_{j,l}(n) = 2^{-j/2} \Psi_{l}(2^{-j/n} - l)$ is the discrete wavelet.

The selection of a particular wavelet function that matches closely to the morphology of the signal under consideration is the most important factor for signal decomposition [21-22]. In pre-processing stage, the noises have been eliminated by decomposing; non-informative frequency components with multiresolution wavelet transform using daubechies (db6) to enhance the important morphology of the QRS complex of ECG signals. The signal is enhanced by eliminating noise with corresponding detail coefficients from high frequency ranges at D1, D2 and low frequency ranges at A10.

$$\Psi_{a,b}(t) \equiv \frac{1}{\sqrt{a}} \Psi^*\left(\frac{t-b}{a}\right)$$
3. Hilbert transform

The proposed method is described in a very convenient manner to detect R peaks efficiently. A real valued time function is $y(t)$, and the Hilbert transform of the given signal is

$$x(t) = H[y(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} y(\tau) \frac{1}{t-\tau} d\tau$$

(4)

Hilbert Transform exhibits the property of time dependency because the independent variable is not changed in accordance with the transformation. And this relation is coming from the convolution computation;

$$x(t) = \frac{1}{\pi} * y(t)$$

(5)

$$F[x(t)] = \frac{1}{\pi} F\left(\frac{1}{i}\right) F[y(t)]$$

(6)

$$F\left(\frac{1}{T}\right) = -j \text{sgn} f$$

(7)

Here $\text{sgn} f$ is $+1$ for $f > 0$; $0$ for $f = 0$; $-1$ for $f < 0$

Putting the equation (4) and (5) in equation (3), we get

$$F[x(t)] = -j \text{sgn} f F[y(t)]$$

(8)

The input-output relationship of Hilbert Transform is the transformation of linear function, hence it acts like a linear filter in which all amplitudes of spectral components are remaining same where the phases are changed with $\pm(\pi/2)$.

Since it is the frequency domain analysis, the spectrum of $y(t)$ is multiplied with $+j$ with the phase shift of $(+\pi/2)$ for $(+ve)$ frequencies and multiplied with $-j$ with the phase shift of $(-\pi/2)$ for $(+ve)$ frequencies. But if we want the output in time domain representation, we have to find out the Inverse Fourier Transform of the real valued signal $y(t)$ because $x(t)$ is represented as the harmonic conjugate of the Hilbert transform of original signal. The pre-envelope signal or the analytic signal comprises of $y(t)$ and $z(t)$. The real valued and the Hilbert transformed output signal is expressed as;

$$S(t) = y(t) + jz(t)$$

(10)

$$V(t) = \sqrt{y^2(t) + z^2(t)}$$

(11)

$$\varphi(t) = \arctan \left( \frac{z(t)}{y(t)} \right)$$

(12)

where $V(t)$ is the envelope of $y(t)$ and $\varphi(t)$ is instantaneous phase angle.

4. Detection of R-peaks using Adaptive thresholding

The R-wave positions of ECG signals are identified as the maximum amplitude points of the de-noised signal. Detection of the R - wave algorithm is summarized as: first the predefined function of Hilbert transforms $b=\text{R_val}$ is normalized. Then the adaptive threshold [23] value of ‘Thy’ (Fig.1) is localized within the QRS region in the function ‘b’. Within the predefined window (160 ms) it searches the first point where the amplitude of function ‘b’ becomes greater than the threshold level. The R-peak positions are identified as the points with the maximum amplitude of the de-noised signal. A refractive period of 200ms between two consecutive searches is considered. Finally the indexes corresponding to the various detected positions are stored in a new array named Rloc. Fig.2. illustrate the block diagram of the proposed algorithm with the process of finding TP, FP and FN.

The detail steps of proposed method as follows:-

1. First the ECG signal is extracted from the MIT-BIH arrhythmia database.
2. Then the signal is de-noised by wavelet transform.
3. The enhanced signal undergoes to the differentiation to maximize the R-peaks with zero-crossing on x-axis.
4. The differentiated signal is processed by Hilbert transform to provide a region of finding real QRS complex.
5. The envelope of Hilbert transformed signal is determined by using equation (11).
6. Finally the true R-peaks are detected by using an adaptive thresholding technique.

The show of the proposed algorithm for QRS detection is evaluated for the sensitivity (Se), the positive predictivity (PP), classification accuracy (Acc) and the detection error rate (DER) using the following equations

$$\text{Se}(\%) = \frac{TP}{TP+FN} \times 100\%$$
$$\text{P +}(\%) = \frac{TP}{TP+FP} \times 100\%$$
$$\text{DER}(\%) = \frac{FP+FN}{TP} \times 100\%$$

where $TP$=True positive is the correct detected R-peaks, $FN$=False negative is the undetected R-peaks, $FP$ = False positive is the mis-detections, $TN$ = Number of true negative beats.
Fig. 1. Flow diagram of adaptive thresholding technique

Fig. 2. Block diagram of the proposed method for the detection of QRS complex
5. Results

The proposed Hilbert transform with adaptive thresholding technique is tested on nineteen recorded ECG signals from the MIT-BIH Arrhythmia database according to the method presented in Figure 2. Figure 3-8 shows the result of record number 103 according to proposed methodology given in the flow diagram (Fig.2) using MIT-BIH database. The performance of the proposed method is evaluated with sensitivity (Se), Positive predictivity (P+) and detection error rate (DER). Table 1 summarizes the QRS detection performance of our proposed method using Hilbert transform with adaptive thresholding. The table 2 summarizes the signal-to-noise ratio, mean square error, mean absolute error and cross correlation. The proposed method detected 44325 beats (DB) from a total of 44329 annotation true beats (TB). It detected true positive of 44207, false-negative beats of 122 and 118 false-positive beats. The proposed method gives the sensitivity (Se) of 99.71% and positive predictivity (P+) of 99.72%, respectively with a detection error rate of 0.52%. We have also found better performance of the method to reduce noise in the signal with an average of 22dB, 0.4, 0.63 and 0.94 for SNR, MSE, MAE, X-corr respectively. A comparative performance of different published results to detect QRS complexes is summarized in table 3. It is evident that the proposed method detects QRS complex effectively as compared to other published results.
Table 1 Extracted parameters of the proposed method using MIT-BIH database

<table>
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<tr>
<th>Record No</th>
<th>Total Beats</th>
<th>Detected beats</th>
<th>TP</th>
<th>FN</th>
<th>FP</th>
<th>Se (%)</th>
<th>P+ (%)</th>
<th>False Detection (FP+ FN)</th>
<th>DER(%)</th>
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<td>0</td>
<td>0</td>
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<td>1866</td>
<td>1863</td>
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Total 44329 44325 44207 122 118 99.71 99.72 236 0.52
Table 2. Performance measures of QRS complex detection

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<th>MSE</th>
<th>MAE</th>
<th>Cross Correlation</th>
<th>Record No.</th>
<th>SNR</th>
<th>MSE</th>
<th>MAE</th>
<th>Cross Correlation</th>
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Average  

Table 3. Performance comparison of record no. 105 with published results

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<th>Method</th>
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<th>FN</th>
<th>Se (%)</th>
<th>P+ (%)</th>
<th>False Detection (FP+ FN)</th>
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5. Conclusion

The recorded ECG signal contains both high and low frequency components that makes difficult to extract QRS complex and other distinguished features. Hence, an adaptive approach can be a better option for de-noising the ECG signals along with the time-frequency analysis. In this paper, a discrete wavelet transform based technique has been used to enhance the operation for QRS detection and then Hilbert transform algorithm with adaptive thresholding is used for detecting QRS complex and R-peak detection in ECG signals. The method is tested with ECG signals in normal and disease conditions. The result found to be better in terms high SNR with less mean square errors (MSE) and the R-peaks has been detected with high sensitivity of 99.71% and the positive predictivity of 99.72% respectively with less detection error rate of 0.52%. Thus it is concluded that the Hilbert transform combined with adaptive thresholding could be used as an efficient approach to detect the R-peaks of the ECG signal for providing useful physiological information for diagnostic of cardiovascular disease.

References