



Research Article

A Wavelet based Method for QRS Complex Detection

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Abstract

ECG signal plays an important role in the diagnosis and analysis of heart diseases and allows the assessment of cardiac muscle functionality. The main and most obvious part of electrocardiography tracing is its QRS complex which corresponds to the ventricular depolarization. The morphology of QRS complex and its repetition are important issues in the analysis of heart diseases so its detection is important for such analysis. In this paper an algorithm based on the multiplication of wavelet coefficients is presented to find out the R peak in ECG for QRS complex detection. The proposed method is based on the band-limited properties of QRS waveform. The ability of proposed method has been evaluated through the comparison with traditional Pan-Tompkins algorithm by standard datasets. The results show that the proposed method besides having lower complexity is comparable with Pan-Tompkins method.

Keywords: Electrocardiography, QRS complex detection, Wavelet Transform

Academic Editor: Sihua, PhD, Shanghai Ocean University, China

Received: July 9, 2014; **Accepted:** September 7, 2014; **Published:** September 17, 2014

Competing Interests: The authors have declared that no competing interests exist.

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1. Introduction

An electrocardiogram (ECG) describes the electrical activity of the heart muscles. Heart electrical activity cycle produces a series of waves whose morphology contain information with diagnostic usage. A typical ECG waveform of the cardiac cycle consists of some sub-segments which include P wave, QRS complex, T wave and probably a U wave. The QRS complex reflects the rapid depolarization of the ventricles. As the ventricle has larger muscle mass compared to atria so the QRS complex has larger amplitude than the P wave which is due to atria contraction. Any disease that alters the muscle conduction can change the pattern of ECG and leads to cardiac dysrhythmia which is usually called arrhythmia. To assess the status of heart functionality it is necessary to extract heart beat for morphology or heart rate variability analysis.

So far several algorithms have been proposed for QRS detection. The most famous algorithm for QRS detection is the algorithm proposed by Pan and Tompkins [1]. This algorithm consists of passing ECG signal successively from some blocks consist of band pass filter, differentiator and then squaring blocks. The band pass filtering removes baseline wander and the high frequency noise from original ECG signal and the differentiator preserves the information about the QRS complex slopes. The squaring helps to emphasize the differences between QRS complex with P and T waves. To smooth the output of squaring it is passed through a moving average block. The two levels adaptive thresholding specifies the locations of QRS complexes in the raw ECG data. As QRS complex includes high frequency content of ECG beat, so derivative methods as a high pass filter can amplifies the QRS complex while attenuates the lower frequencies components like P and T waves. The first derivative methods which needs lower computational complexity are favorable for real time analysis or applications consisting of large datasets. Such methods needs no manual segmentation and algorithm training steps [2].

The template matching methods have gained attentions in QRS detection. In this regard the correlation coefficient is a value that exhibits the amount of similarity between a predefined template and intended QRS event in signal. A QRS detection technique was proposed by Dobbs *et al.* which used cross-correlation [3]. Although such methods can be implemented in real-time but correct template selection is a crucial issue which needs a-priori knowledge about the intended QRS complex event. An algorithm based on the properties of Hilbert transform was proposed by Benitez *et al.* [4]. The Hilbert transform is an all-pass filter with $+90^\circ$ shift for negative frequencies and -90° shift for positive frequencies. The all-pass properties of this transform guarantees that no distortion occurs in the transformed signal. In the method proposed in [4] the effects of the Hilbert transform on the differentiated ECG were explained in terms of its odd symmetry property and signal envelope. Another algorithm based on Hilbert transform was proposed in [5] which used Hilbert transform as a zero crossing detector in differentiated ECG signal. The R peak locations in differentiated ECG signal creates zero crossing which produces peaks in the output of Hilbert transform as the phase changes in the zero crossing.

The ability of wavelet transform is examined in different works for QRS detection [6-8]. The multiresolution wavelet transform can reveal the distribution of signal energy in different time and frequency resolutions. As the energy content of QRS complexes may differ with non-QRS events so this differences can be used to detect QRS events in ECG signal [8]. So focusing on power spectrum of QRS complexes in different energy levels of multiresolution wavelet makes this possible to separate different morphology(normal vs. abnormal) from each other. For preprocessing aims and in the aim of noise reduction the wavelet-based threshold estimation can be incorporated [7].

In this paper a method based on wavelet transform is proposed for noise reduction and QRS complex

detection which uses the band-limited properties of QRS complexes by multiplication of wavelet coefficients in some limited numbers of detail levels. The results show that high probability of correct detection and low probability of false alarms are achieved.

2. Material and methods

2.1 Multiresolution Wavelet Transform

Wavelet is a brief wave-like oscillation which has special properties that make it suitable for signal processing purposes. It has compact support in time domain and is band-limited in frequency domain which enable it to obtain better time and frequency resolutions compared with traditional Fourier transform. Wavelet transform is the representation of a function by wavelets. This can be achieved by the convolution of wavelet basis function and intended signal. If there is an event in the signal with similar morphology as wavelet basis function, like QRS complex, a peak will appear in the convolution result so the wavelet transform can be considered in a template matching procedure. In this manner wavelet transform can be used for QRS event detection. In multiresolution wavelet transform, the intended signal is passed successively through the low and high pass filters that are defined by wavelet and scale functions. The outputs of high pass filter are detail coefficients and contain the detail information about intended signal and the outputs of low pass filter are approximate coefficients which show the approximate variations in the intended signal. For extracting further information of signal, the high pass and low pass filters are applied to the approximate coefficients again and this continues for several steps. As in each step the band width of detail and approximation coefficients are reduced to half so for avoiding redundancy, down-sampling is carried out. The detail coefficients of different steps contain the detail information with different resolutions. In this manner multiresolution wavelet transform creates a time-frequency representation of intended signal.

2.2 Proposed method

The main idea of the proposed method for QRS complex detection based on the multiresolution wavelet transform is that QRS complex is a band limited waveform so its representation in time-frequency wavelet domain concentrates in the limited successive number of scales which may be different from other waves of ECG beat, like P and T waves. Also it should be noted that the events projection in different scales are localized in time. This means that the QRS energy in each successive scale is concentrated around a specific time location. Therefore it is possible to implement a QRS detection method based on the multiplication of wavelet coefficients in the limited number of successive scales. This multiplication emphasizes QRS complex and attenuates other waves. Although such multiplication deemphasize uncorrelated events and in this way some kind of denoising is carried out. In this paper instead of traditional discrete wavelet transform (DWT), undecimated wavelet transform (UWT) framework has been used which is similar to DWT but contains no down-sampling. In this way UWT contains more coefficients than DWT and it has shown to be more suitable for event detection compared with DWT [9]. Details of the proposed wavelet QRS detection method is as follows:

1. The wavelet decomposition of ECG signal in UWT framework is carried out. Based on the literature the lower and upper band width of baseline wander as a low frequency unwanted fluctuation are about 0.015 and 0.03 Hz, respectively [10]. The baseline is usually replicated in the detail and approximation coefficients of the last level so for removing baseline wander and other unwanted low frequency components, the scale and detail coefficients in the last level are removed from further

analysis. To avoid removing ECG related coefficients, number of decomposition levels is calculated based on the baseline wander frequency characteristics. For this purpose (1) has been used.

$$n = \text{round}\left(0.5\log_2\left(\frac{f_{\max}}{\Delta f_{\text{BWH}}}\right) + \log_2\left(\frac{f_{\max}}{\Delta f_{\text{BWL}}}\right)\right) \quad (1)$$

Where f_{\max} is the sampling frequency of ECG signal, Δf_{BWH} and Δf_{BWL} are usual upper band width and lower band width of baseline wander.

- The detail coefficients of scale 1 up to 3 are selected. It should be noted that QRS complex in most cases has higher frequency content and bandwidth than T or P waves so it is projected in the primary detail levels. Before multiplication of selected levels, two further preprocessing task are considered. For removing small amplitude fluctuations which aren't related to high energy QRS complex events, each selected scale is smoothed by Blackman-Nuttall window through convolution. The Blackman-Nuttall window has the widest main lobe and the lowest maximum side lobe level in comparison with other selections like Hamming or Hanning windows. This causes lower distortion in the signal. Furthermore an estimation of background noise is obtained based on the median absolute value of wavelet coefficients in the selected detail levels [9]. Based on the estimated noise level, a threshold calculated for each scale and soft thresholding is carried out for each scale. The noise level estimation(σ) and threshold selection(T) is done according to (2)

$$\sigma = \text{median}|d_i - \text{median}(d_i)|/0.6745 \quad (2)$$

$$T = \sigma\sqrt{2\log_e(N)}$$

In (2) d_i is the detail coefficients in i -th scale and N is the length of ECG signal. Estimating a threshold level by (2) has lower sensitivity to outliers [9]. It should be noted that due to removing down-sampling step in UWT, the length of signal and all detail and approximation levels in UWT are the same. The background noise has different origins like electrode displacement or the noise induced by electronic recording devices.

- After two preprocessing steps, the absolute value of the coefficients in selected detail levels($W(2^j, n)$) are multiplied in a point-wise manner as (3):

$$A(n) = \prod_{j=1}^3 |W(2^j, n)| \quad (3)$$

- For removing spurious peaks due to cross terms, $A(n)$ is smoothed again by a Blackman-Nuttall window.
- To find the location of R peaks of QRS complexes, a peak detection procedure in multiplication output is carried out. Here the adaptive tresholding of Pan-Tompkins algorithm is used [9]. This procedure determines thresholds by computing running estimates of signal and noise peaks. Each detected peak, is R peak if crosses two distinct threshold levels. The peak levels and thresholds will be updated after each peak is detected. Each R peak specifies one QRS complex.

To assess the ability of proposed method for QRS detection, it has been compared with traditional QRS detector i.e. the one proposed by Pan-Tompkins [1]. The criteria for evolution are the probability of False

alarms (P_{FA}) and the probability of correct detection (P_{CD}) which are defined as follows:

$$P_{CD} = \frac{N_{CD}}{N_{QRS}} \times 100 \quad (4)$$

$$P_{FA} = \frac{N_{FA}}{N_{CD}} \times 100$$

Where in (4) N_{CD} is the number of correctly detected complexes, N_{QRS} is the number of QRS complexes in ECG signal and N_{FA} is the number of falsely detected complexes by algorithm. In the dataset used for evaluation purposes the exact time of QRS complexes and N_{QRS} are known.

2.3 Data description

The datasets used for performance evaluation is borrowed from Physionet dataset¹. This is MIT-BIH Normal Sinus Rhythm Database(nsrdb). The nsrdb sampling frequency is 128 Hz with 12 bit resolution that contains 18 recordings which 10 of them have been used for analysis. Most of the ECG beats of recordings are normal beats. The length of each examined recording is 1 hour. Number of R peaks and their locations in each recording are known.

3. Results and discussion

The main concept of proposed wavelet based method is depicted in Fig.1. The raw ECG signal (panel A) is decomposed in 9 levels which 5 of them are depicted in panels B-F. The multiplication is depicted in panel G. The dashed rectangle shows one QRS complex and its corresponding traces in wavelet detail levels and also multiplication result. Note that the QRS energy mainly spreads in some successive limited number of detail levels. As the QRS complex has the highest frequency content in ECG beat so it is mainly projected in the primarily detail levels. In this way the multiplication of such detail levels helps the QRS complex to be emphasized and other components which have different energy (frequency) contents to be deemphasized.

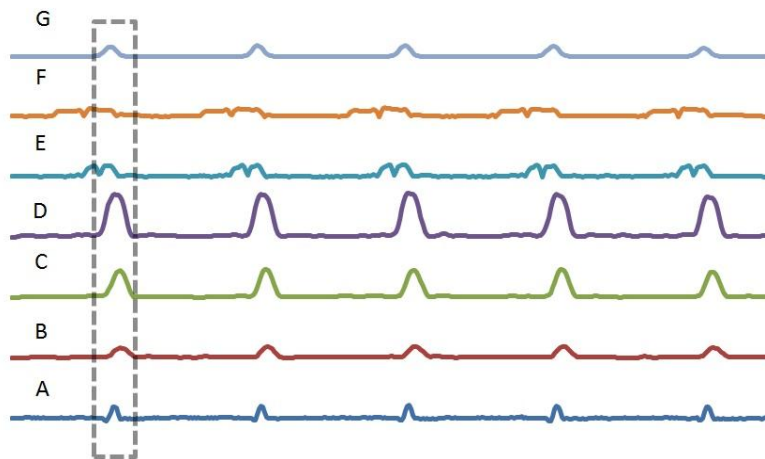


Figure 1 Multiplication of wavelet detail coefficients for QRS detection. (A) main signal, (B-F) wavelet detail scales 1-5, (G) multiplication result of first three detail scales. Note to the alignment of QRS complex traces in dashed rectangle. The multiplication amplitude has been normalized.

¹ <http://www.physionet.org/cgi-bin/atm/ATM>

The results of QRS detection for nsrdb dataset (see section 2.3) for proposed wavelet based method and Pan-Tompkins algorithm are reported in Tab1. Higher P_{CD} and lower P_{FA} indicate the higher performance of algorithm.

Table 1 Comparison of the proposed method and Pan-Tompkins algorithm for QRS detection.

Recording	Number of beats	Pan-Tompkins		Wavelet-based detection	
		$P_{CD}\%$	$P_{FA}\%$	$P_{CD}\%$	$P_{FA}\%$
16265	5268	100	0	99.89	0
16272	3450	91.94	9.82	95.16	3.39
16273	3451	98.94	0	99.87	0
16483	5675	100	0.22	99.74	0.11
16539	4756	96.63	2.33	96.26	1.2
16773	4256	99.35	0.7	99.47	0.6
16786	4406	98.53	0	98.67	0.63
17052	4465	98.57	1.56	99.14	1.47
18177	5826	96.92	6.35	96.31	3.33
18184	5206	100	0	100	0
average		97.86	2.09	98.45	1.07

For recording number 16272, where the T wave has considerable amplitude compared with other recordings, both algorithms have high false alarm rate because the T wave trace in Pan-Tompkins and wavelet-based method output crosses the thresholds and are considered as QRS complex. Although such high amplitude T waves increases the threshold levels and therefore some QRS complexes will be lost. These results show that the average P_{CD} is higher and its average P_{FA} is lower for wavelet-based method. In the Pan-Tompkins algorithm the edge of low and high pass filters determines the unwanted fluctuations which have different frequency contents from ECG waves but if the artifact content overlaps with ECG waves it is difficult for Pan-Tompkins algorithm to remove the artifact. In the proposed wavelet multiresolution procedure the low frequency artifacts are removed by discarding last detail level and approximation levels and the high frequency noise will be discarded by soft thresholding on detail levels. Also the multiplication will emphasize the events which are localized in time and are band-limited. In this way the attenuation of artifacts which have common frequency with ECG waves is possible and this leads to lower false alarm rates for proposed wavelet-based method.

Also the robustness of both algorithms against noise is evaluated. For this purpose “St Petersburg INCART 12-lead Arrhythmia database” is used which is accessible through Physionet database. The lead II of record I01 which is a noisy recording is used. This data is depicted in Fig.2 (upper panel). The locations of R peaks which are specified in data description are shown by empty circles. The result of R peak detection using Pan-Tompkins algorithm and the proposed wavelet-based method are shown with the threshold levels (signal level, noise level and adaptive threshold level). It is clear that the wavelet-based method as well as

Pan-Tompkins algorithm detects true locations of R peaks. Note that in Pan-Tompkins algorithm the peak locations are found with some delays while the wavelet based method finds the peaks in their exact locations(Fig2. B).

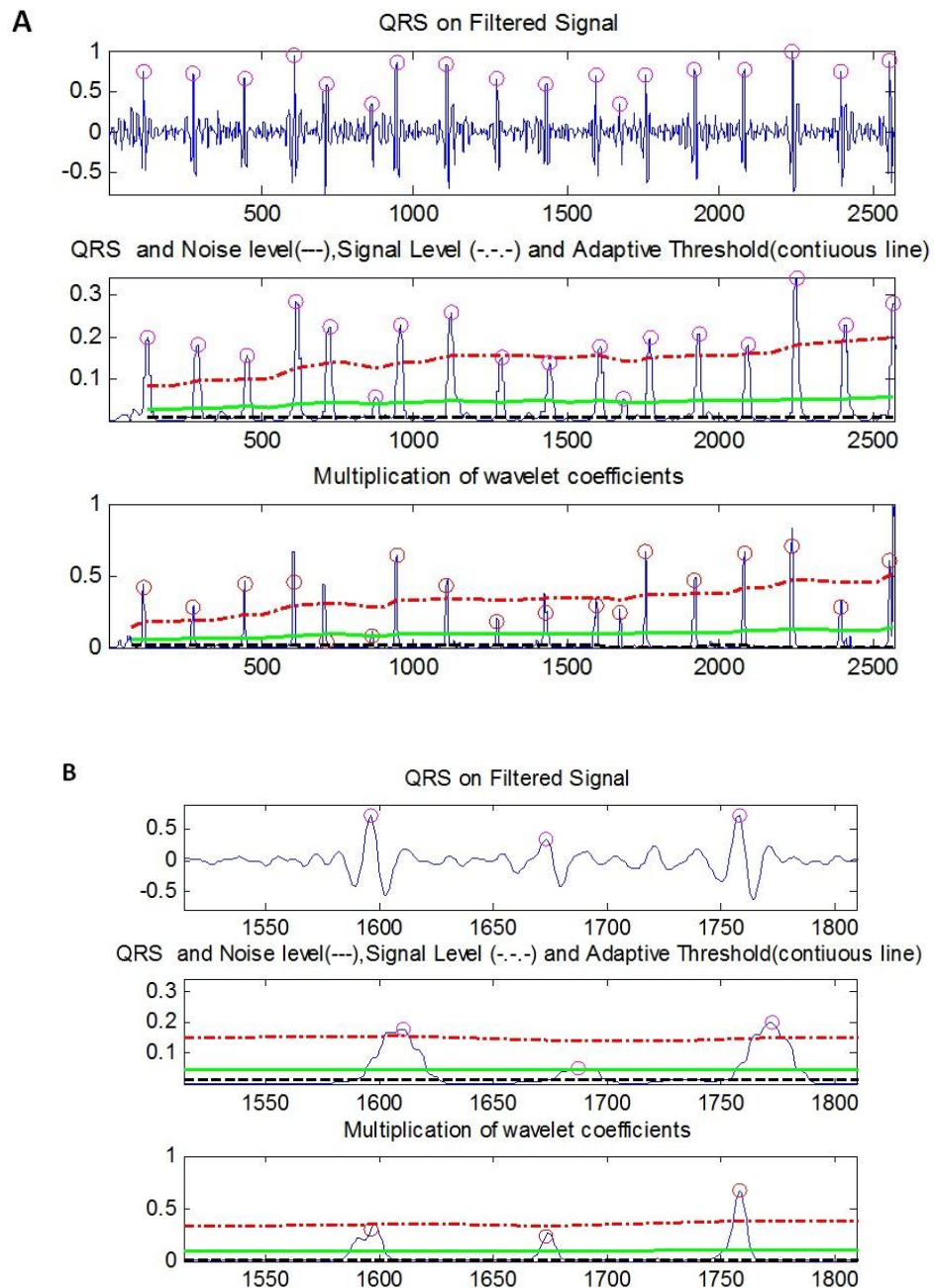


Figure 2 (A) Comparison of the proposed multiplication procedure and Pan-Tompkins algorithm for a noisy arithmetic ECGdata(St Petersburg INCART 12-lead Arrhythmia database from Physionet database). The lines in the figure are noise level (---), signal level (-.-.-) and adaptive threshold(continuous line). The circles are R-peak locations which for upper panel are specified by dataset. (B)In the lower plot, a segment of the result has been enlarged. Note that the Pan-Tompkins algorithm finds R peaks with some delays.

4. Conclusion

Analysis of ECG signal is important for assessment of the healthy functionality of Heart. The main part of such signal is called QRS complex which contains the majority of ECG energy. To detect such part of ECG signal several algorithms have been proposed so far. In this paper a method based on the multiplication of wavelet coefficients has been proposed for QRS detection. The proposed wavelet based method accounts the band-limited properties of ECG different waves which causes the different waves to be projected in different scales in the time-frequency representation of wavelet transform. Selecting some limited number of successive scales and multiplication of them, after some pre-processing steps emphasizes the QRS wave and deemphasize other waves. The results indicate that the proposed method is comparable with traditional Pan-Tompkins algorithm. The result show that for MIT-BIH Normal Sinus Rhythm Database (nsrdb) the proposed wavelet based method results higher average for correct detection rate and lower average for false alarm rates compared with Pan-Tompkins method.

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