

Automatic detection of QRS complex based on wavelet transform and cluster analysis

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Abstract

The paper briefly the idea of designing an algorithm for automatically locating the QRS complexes in the single-lead ECG signal based on continuous wavelet transform (CWT) and cluster analysis. The local QRS complexes are first detected in the transformed signals at three different scales. The global QRS complexes were then determined from separate locations in the transformed signals by using a cluster analysis method. The proposed algorithm was evaluated on the two-lead ECG database (MIT-BIH Arrhythmia Database), which contains global reference positions common for all lead.

Key Words: ECG, continuous wavelet transform, cluster analysis, MIT-BIH ST Change Database.

I. Introduction

Electrocardiogram (ECG) is a nearly periodic signal that reflects the activity of the heart. Much information on the normal and pathological physiology of heart can be obtained from ECG. Therefore, the features extracted from the ECG signal are significant for the doctors as a guide to correct clinical diagnosis [1].

Many studies have been done in the field of ECG signal analysis using various approaches and methods for the past three decades. The basic principle of all the methods involves the transform of ECG signal using different transform techniques including Fourier Transform, Hilbert Transform, Wavelet Transform, etc. Pan and Tompkins [2] proposed an algorithm (the so-called PT method) to recognize the QRS

complexes. In [3], the authors have been implemented as a method to detect the ECG beat using Geometrical Matching Approach algorithm. Based on the estimation of the first-order derivative, the slope vector form algorithm has also been proposed in [4]. However, the ECG signals are considered to be a quasi-period that is of finite duration and non-stationary; it is challenging to analyze them visually. Hence, a technique like Fourier series (based on sinusoids of infinite duration) is inefficient for ECG.

On the other hand, wavelet transform (WT), which is a very recent addition in this field of research, provides a powerful tool for extracting information from such signals. There has been the use of both continuous wavelet transform (CWT) as well as discrete wavelet transform (DWT). However, CWT has some inherent advantages over DWT. Unlike DWT, there is no dyadic frequency

jump in CWT. Moreover, the high resolution in the time-frequency domain is achieved in CWT [5].

The paper is organized as follows: in Section II, we present the materials and the QRS complex detection method. The results of the validation on the MIT-BIH Arrhythmia Database in Section III. Finally, the conclusions are presented in Section IV.

II. Materials and Methods

The proposed algorithm for the detection of the QRS complex is presented in Figure 1. This method includes signal preprocessing, continuous wavelet transforms, thresholding and identification of local QRS complexes, and determination of global QRS complexes using cluster analysis. The detail of each phase is described in the following sections.

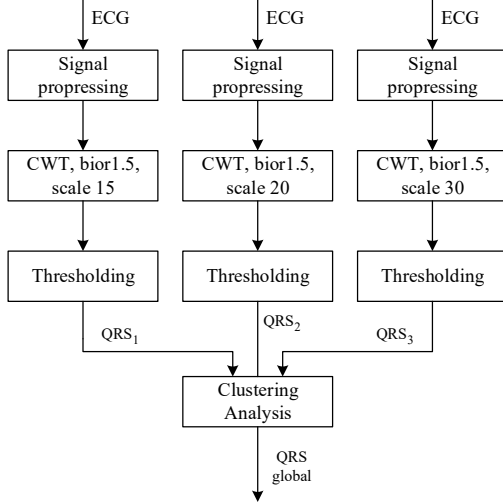


Figure 1. Block diagram of the proposed method for the detection of the QRS complexes.

1. Signal preprocessing

In this phase, the ECG signal was divided into the 4096-sample segments by a sliding window. The incomplete QRS complexes located at the end of the 4096-sample segments can be misidentified as Not QRS peaks, so an overlap of 150 samples has been designed to overcome this problem. Thanks to the 150-sample overlap, these unfinished

QRS complexes can be included entirely at the beginning of the next segment. We used then two median filters to remove the low-frequency baseline drift [6]. Each segment was first filtered by a median filter with a width of 200 *ms* to remove the QRS complexes and P waves, the resulting signal was then filtered again by a median filter with a width of 600 *ms* to eliminate the T waves. Therefore, the baseline drift noise can be extracted by the output of the second median filter, and the baseline drift eliminated ECG signal can be obtained by subtracting the estimated baseline drift signal from the original ECG signal.

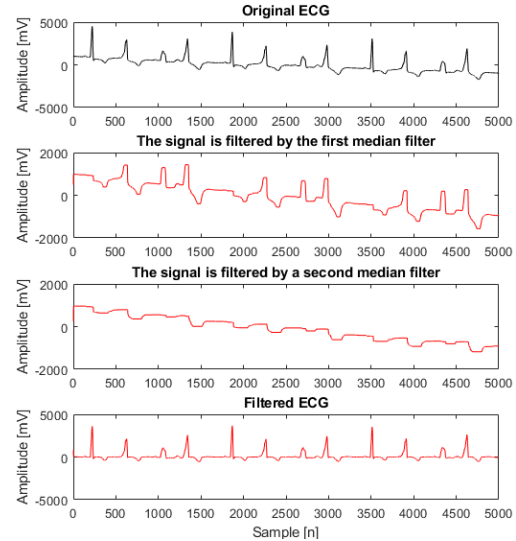


Figure 2. Illustration of removing the low-frequency baseline drift noise.

2. Continuous wavelet transforms

Wavelets are a powerful tool for the representation and analysis of physiological waveforms like ECG, etc. [5], [7]. They provide both time and frequency view. Unlike the Fourier transform, the WTs are very efficient for non-stationary signals like ECG. In WT, a fully scalable modulated window is used to solve the signal-cutting problem. The window is shifted along with the signal. Spectrum is calculated for every position. This process is repeated by varying the length of the window. The result is that

we have a collection of representations, hence the name multi-resolution analysis.

In this work, the CWT is applied to decompose the ECG signal into a set of coefficients that describe the signal frequency content at given times. The CWT of the continuous signal, $x(t)$, is defined as

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

where $\psi(t)$ is a continuous function called the mother wavelet, and the asterisk denotes the operation of the complex conjugate.

To implement the proposed algorithm, each filtered signal segment is transformed into the wavelet domain by CWT at an appropriate mother wavelet and scales. The most commonly used types of mother wavelet for detecting the QRS complexes are the quadratic spline function [8], [9] and the first derivative of the Gaussian function [10]. However, the mother wavelet used in this work is the biorthogonal family, namely *bior1.5*. The wavelet *bior1.5* is an odd-symmetry wavelet that transforms the extremes of the original signal into zero-level passages and transforms the inflection points into extremes. Moreover, instead of finding for similarities across the other dyadic form of discrete-time wavelet transforms (DyDTWT) scales as in [8], [9], the proposed algorithm used appropriate scales. The best results were achieved with scales such as 15, 20, and 30.

3. Thresholding and identification of the local QRS complexes

The output from the CWT phase is signals transformed at three different scales 15, 20, and 30. For each of these transformed signals, the algorithm will then find pairs of near opposite sign extremes, whose absolute values are higher than the threshold ξ_{QRS} . If such pairs of extremes are found, and if these extremes are spaced less than the refractory period, 120 ms, then the positions of these extremes correspond to the ascending and descending edges of several of the QRS

complexes. The position of the waves is then determined by the zero-crossing position between the two adjacent extremes. In this way, one or more candidates of the QRS complex can be detected. Because the detection indicates the position of the complex as a whole, it is necessary to identify a unique exact position representing the QRS complex. Therefore, there is a refractory period, 120 ms, before the next one can be detected since the QRS complexes cannot occur more closely than this physiologically. The positions preceded by another position in an interval shorter than this refractory period are removed from the detected positions. Therefore, the position of the QRS complex is the position of the first detected wave within candidates of the complex. The threshold level, ξ_{QRS} , is given by the equation,

$$\xi_{QRS} = K \cdot \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

and thus, the threshold level corresponds to K times the standard deviation calculated from all the values of the transformed signal. In this work, the constant K was determined as a suitable factor of the standard deviation based on the analysis of the complete ECG signal database (highest detection rate) and is 1.3. Deriving a threshold level from a standard deviation is a more robust approach than once derived from the maximum value or the difference between the maximum and the minimum values that can easily be affected by the artifact or extrasystoles. The threshold level is fixed and is the same for the entire segment of the analyzed signal.

From the position of the detected QRS complexes in the signal segments, the local QRS complexes of the whole signal transformed at a specific scale will again be reconnected by the location of the segments.

4. Determination the global QRS complexes

The reliability of detection will increase significantly if we can combine the complex locations across the individual transformed

signals. The result of such a combination is the global position of QRS complexes that are the QRS complexes to the original signal. This algorithm used to combine the local QRS complexes here is cluster analysis.

The term cluster analysis refers to a variety of algorithms and methods for grouping similar objects into clusters. The similarity between the objects of one cluster should be as large as possible, and the similarity between objects belonging to different clusters is as small as possible. The clustering method used by us is one of the so-called hierarchical agglomerative methods that are based on individual objects, and their sequential clustering creates a hierarchical tree structure ending with a single cluster of all objects. The clustering of objects in more massive clusters is based on the measurement of similarities or distances between objects.

In this study, we used the clustering-based method taken from [11], [12], and [13]. The input of the used method is the position of all detected QRS complexes in the individual transformed signals. A matrix of Euclidean distances is first calculated between all possible pairs of QRS complex positions. Besides, a hierarchical tree structure is created, and for the clustering itself, the nearest distance method is used. The cluster parameter of this method is the smallest distance between two objects of different clusters. The set of clusters is then selected from the tree structure that meets the specified criterion. The criterion used here was the minimum distance of adjacent clusters of 100 ms.

The obtained clusters represent candidates for global QRS positions. Clusters containing fewer objects than half the number of scales is excluded from the set of clusters. These clusters are considered to be false detection. From the remaining clusters, global QRS complex positions are determined based on median positions within each cluster.

III. Results and Discussions

This section will present the results of the QRS complexes detection on several signal segments from the MIT-BIH Arrhythmia Database. At the top of each figure, short red lines are used to denote the detected QRS peaks. FP denotes a false positive peak. Figure 3 shows the QRS complex detection results for a high-noise ECG signal from recording 104. From the figure, we can see that if the detection of QRS peaks is based on CWT at scale 15, several peaks are misidentified as QRS peaks, as shown in the top figure of Figure 3. If the detection of QRS peaks is based on CWT at scale 20 or 30, all QRS peaks are identified accurately, as shown in the middle two images of Figure 3. These local QRS complexes achieved at each scale were then used as the input to the cluster analysis algorithm. As a result, the global QRS complexes have been correctly identified despite the high-noise in the signal.

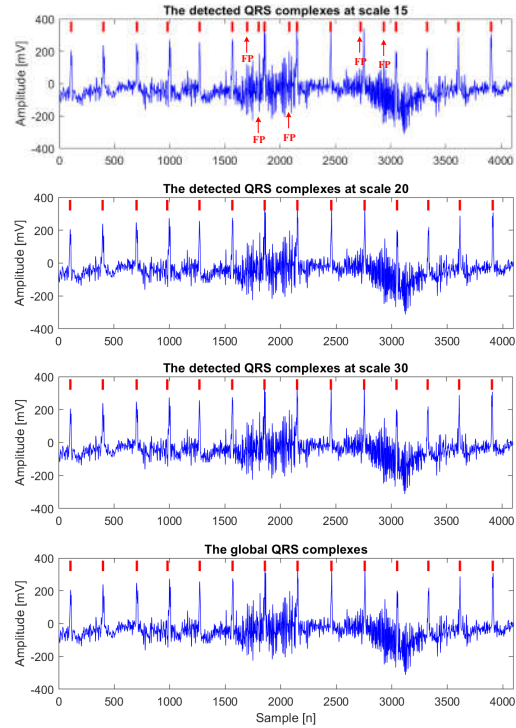


Figure 3. Illustration of the QRS detection results for a noisy ECG signal (take from recording 104).

From Figure 4, the results indicate that the

proposed algorithm succeeded in finding a QRS peak with a significantly reduced amplitude compared to the two adjacent QRS peaks (6th peak). This beat is the peak of a Ventricular Premature Contraction (VPC) beat.

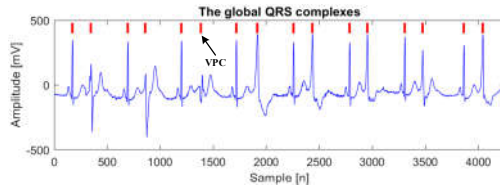


Figure 4. Illustration of the detection failures caused by significantly reduced amplitudes of QRS peaks compared to the adjacent QRS peak (take from recording 106).

Besides the above results, the proposed algorithm still has some limitations. Figure 5 shows the detection failures caused by large-amplitude artifacts. It is evident that the three peaks of large-amplitude noises are very similar to QRS peaks and are misidentified as QRS complexes. Figure 6 illustrates the detection failures caused by a P-peak sharper than the QRS peak. When a P- or T-peak is sharper than a QRS peak, it can cause detection failures.

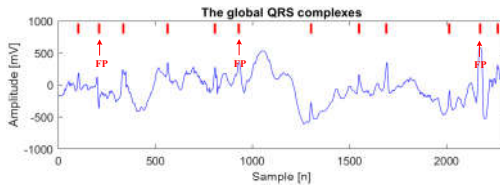


Figure 5. Illustration of the detection failures caused by large-amplitude artifacts (take from recording 105).

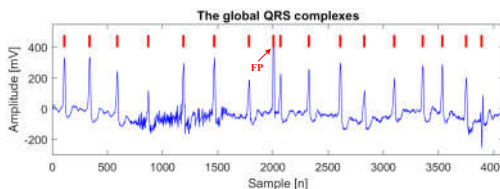


Figure 6. Illustration of the detection failures caused by the P-peak being sharper than the QRS peak (take from recording 203).

IV. Conclusion

This paper proposes a QRS complex

detection algorithm based on a continuous wavelet transform. The identification of QRS complexes was based on the extremum pairs in the wavelet coefficients and the proposed decision rules (cluster analysis). The performance of the proposed algorithm has been tested on several pieces of data in the MIT-BIH arrhythmia database and yielded good results despite some limitations.

V. Acknowledgment

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