A Semi-Automated QT Interval Measurement Based on Wavelet and Energy Analysis

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Abstract

In this paper, a semi-automated multiscale algorithm based on rescaled continuous wavelet transform is presented in order to determine QT interval. According to our previous works, the relation between the duration of ECG waves and their wavelet transforms and dominant scales are used to determine QRS complex vicinity and to denoise ECG signal based on detected vicinity of QRS complex. Then, a simple mathematical sinusoid model for T-wave is considered to determine T-wave domain which is based on variance deviation of T-model and ECG between two successive QRS complexes. A simple analysis of signal's energy leads to rescaled Maximum Energy Density (MED) curve which is used to determine onset and offset of QT-interval. We evaluated the algorithm on the PTB database. The proposed approach is achieved about 53.7 ms of RMS error. The preliminary results are sent to PhysioNet/Computers in Cardiology Challenge 2006.

1. Introduction

The electrocardiogram (ECG) is an important non-invasive tool for assessing the condition of the heart. By examining the ECG signal in detail it is possible to derive a number of informative measurements from the characteristic ECG waveform. Perhaps the most important of these measurements is the "QT interval", which plays a crucial role in clinical drug trials. In particular, drug-induced prolongation of the QT interval (so called Long QT Syndrome) can result in a very fast, abnormal heart rhythm known as ***torsade de pointes*** [1], which is often followed by sudden cardiac death. Since, changes in the QT interval are currently the gold standard for evaluating the effects of drugs on ventricular repolarization, since the wide variety of changes observed in the morphology of T-wave and its low frequency components, QT interval measurement algorithms have been an intensive research field in the recent years.

In practice, such measurements are carried out manually by specially trained ECG analysts. This is an expensive and time consuming process, which is susceptible to mistakes by the analysts and provides no associated degree of confidence in the measurements. For this reason, much effort has been put into developing automated methods that can accurately and effectively measure the QT interval in ECG waveforms [2].

Currently however, no automated system can achieve the same level of accuracy as an expert ECG analyst. In particular, unusual waveform morphologies (such as those caused by entopic beats) coupled with the various noise processes which affect the ECG (such as muscle artifact and baseline wander), often result in unreliable QT interval measurements by automated techniques.

The vast majority of algorithms for automated QT analysis are based on threshold methods which attempt to predict the end of the T wave as the point where the T wave crosses a predetermined threshold [3]. More recently, Graja and Boucher have investigated the use of hidden Markov tree models for segmenting ECG signals encoded with the discrete wavelet transform [4]. Furthermore, some methods based on wavelet transform (DWT) are developed for QT interval measurement [5-6].

In this paper we propose a new approach to semi-automated QT interval analysis, applied continuous wavelet transform (CWT) analysis employing the Haar wavelet in the exercise ECG signal which produces both a segmentation of the ECG and an associated degree of confidence in the QT interval detection. Such confidence in measurements can be used to assess the novelty of the method under consideration, and thus to determine a suitable threshold for rejecting QT interval measurements which are deemed to be unreliable.

2. Mathematical concepts

2.1 Dominant Scale

In order to analyze ECG signals we introduced rescaled wavelet coefficients, $T_n(a,b)$ (Equation 1), inspiring from wavelet ridge which is used to determine the instantaneous frequencies of signal components in case of Morlet T-wavelet [7].

$$T_n(a,b) = \frac{T(a,b)}{\sqrt{a}} \qquad (1)$$

In order to analyze ECG signals using CWT, we used the simple mathematical model proposed at [8] as shown in Figure 1. In this model, a normal ECG

beat is approximated by the summation of two sinus functions correspond to P and T-waves and three triangles as QRS complex. Regarding to the linearity of Haar wavelet transform, the rescaled wavelet map of the proposed model has been evaluated by transforming each component separately.

Consequently, the duration of each component of an ECG signal is expressed as a function of time interval and the corresponding dominant rescaled wavelet coefficients.

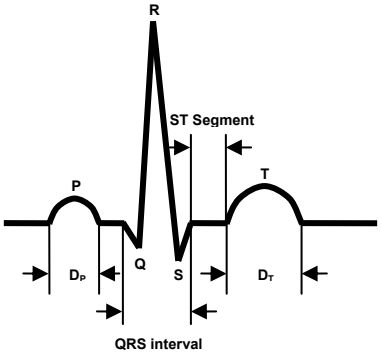


Figure 1. A mathematical model of ECG signal

The following relation between dominant scale and sample time for QRS complex are derived as:

$$a_{QRS} = 1.00\left(\frac{D_{QRS}}{T_s}\right) \quad (2)$$

Where, D_{QRS} is the QRS complex duration and T_s is rescaled wavelet coefficient.

2.2 ECG Denoising

It's possible to eliminate undesired high frequency components, noises, in ECG signal using windowed analysis. By knowing the QRS complexes domain, a window is considered. The scale of this window is defined as a function of QRS dominant scale (Equation 3).

$$f_i(x) = 1 + \left(1.3 \times a_{QRS} - 1\right) \times \left(1 - e^{-\frac{0.02(P_i - x)^2}{a_{QRS}}}\right) \quad (3)$$

Where, P_i is the sample index of i^{th} detected R wave, x is the sample index and a_{QRS} is the QRS Dominant Scale. For sample index of i^{th} detected R wave, x change as:

$$\frac{(P_{i-1} + P_i)}{2} \le x_i \le \frac{(P_i + P_{i+1})}{2} \quad (4)$$

The formula defines window's scale in the vicinity of i^{th} QRS that varies from 1 to $1.3 \times a_{QRS}$. The mean value through the window is set to the signal's value at the center of the window. By this approach, the lowest length, results the original signal. High frequency components including noises and QRS complexes are significantly observed in low scales. In contrast, low frequency components including T and P waves are observed in high scales. Therefore, around QRS complexes, denoised signal is mostly like original signal, and outside the QRS complexes high frequencies are eliminated or weakened. It results a denoised smooth signal and morphologies similar to its original ECG signal. Baseline wandering is also removed by considering local average over two seconds of ECG signal. An empirical ECG Denoising plus baseline-wandering is shown in Figure 2.

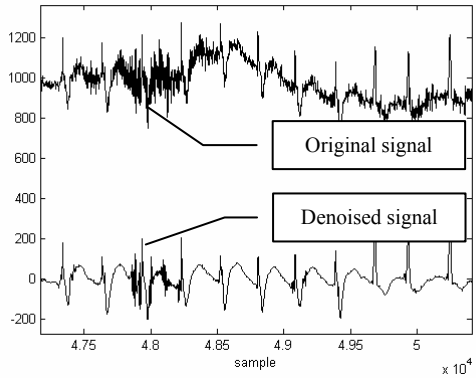


Figure 2. Empirical Denoised ECG signal and baseline-wandering removing (MIT-BIH database; patient 104)

3. Domain Detection Methods

3.1 Threshold based technique of QRS Complex detection

In order to detect QRS complexes, the Haar continuous wavelet transform of ECG signal is used. QRS complex is more significant at its dominant scale, therefore it is sufficient just to analyze the CWT of ECG signal at its QRS dominant scale [9].

The Method is based on threshold Method [10] at which two concepts of local search interval [11] and dominant rescaled wavelet coefficients [8] are used.

The threshold is locally determined for about two seconds of heart-beat according to Equation 5.

$$thresh = \alpha\left(\frac{4}{9}M + \frac{5}{9}R\right) \le M \quad (5)$$

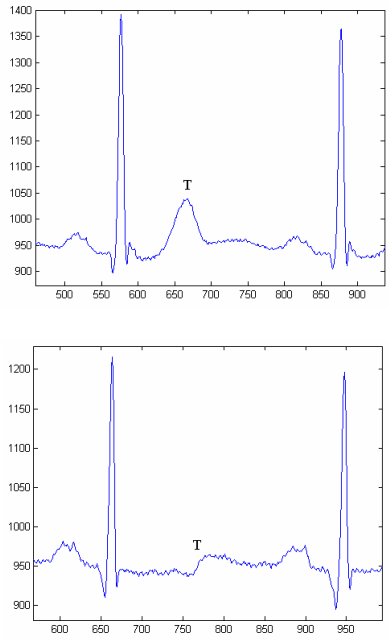
$$1.0 \le \alpha \le 1.25$$

Where R is the local root mean square (rms) and M is the amplitude of local extremum of rescaled CWT and α denotes search back coefficient. The search is initiated at $\alpha = 1.5$. At each search back stage, a lower value for α is considered [10].

3.2 Minimum variance deviation technique of T-wave detection

T-wave is a low frequency wave with rather long duration and mainly, it has two different morphologies (Figure 3). T-wave vicinity can be determined by searching through denoised signal for long duration waves between each pair of detected QRS. In order to determine T-wave domain, first we consider a simple mathematical sinusoid model for T-wave (Figure 1). Then, the variance of ECG signal and modeled T-

wave between two successive detected QRS complexes is calculated. The region, at which this variance becomes minimum, denotes T-wave vicinity [10].



(a)

(b)

Figure 3. Two main morphologies of T-wave

4. Onset & offset estimation technique of QT interval

4.1 Distribution of Energy over time-Frequency space

The contribution to the signal energy at the specific a scale and b location is given by the two-dimensional wavelet energy density function known as the scalogram (analogous to the spectrogram—the energy density surface of the Short Time Fourier Transform (STFT)) [7]:

$$E(a,b) = |T(a,b)|^2 \qquad (6)$$

Where $T(a,b)$ is CWT at scale a and location b. But we are more concern about rescaled CWT and develop it to the energy density surface called rescaled energy density which is defined by Equation 7.

$$E_n(a,b) = |T_n(a,b)|^2 \qquad (7)$$

In each location, b, the value of wavelet becomes maximum in a specific scale or frequency. This scale denotes the dominant scale of the signal in that location, which can be calculated as Equation 8:

$$\frac{\partial E_n(a,b)}{\partial a} = 0 \rightarrow a = a_{domin}(b) \qquad (8)$$

The diagram of the Maximum Energy Density (MED) in the a-b plane can be obtained via plotting a_{domin} with respect to b. In other words, the answer of this question that in what scale the energy density in a specific location reaches to its maximum value is the key point in the mentioned concept. We call the consequent curve 'the rescaled MED curve'. For instance, the rescaled MED diagram of modeled ECG signal is shown in Figure 4:

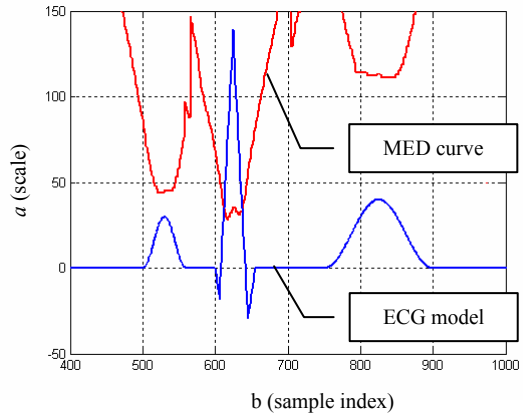


Figure 4. One beat of ECG signal and its MED curve

It should be noted that above definition slightly differs from wavelet ridges which determine regions with a high concentration of energy, not the highest one that the MED curve describes so. This approach inspired from this fact that ECG signal is composed of several instantaneous single-frequencies. As shown in Figure, special waves are obviously distinguishable as sinusoid waves. Therefore, MED curve can be the best candidate to analyze ECG waves such as P and T waves or QRS complex.

4.2 Onset and Offset estimation

Consider a sinusoid T-wave. There are clinical resting levels before and after T-wave in ECG signal, which is called ST segment and TP interval respectively and theoretically, they have zero frequencies. Therefore, the MED curve for T-wave obtained as Figure 5, which a_d denotes the dominant scale of the sinusoid T-wave.

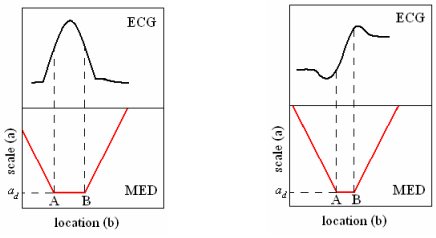


Figure 5. MED curve of two main morphologies of T-wave

Now, we use mathematical approach to determine offset of T-wave. Wherever, the wavelet window reaches to the end of T-wave, MED curve starts to rising up –at point A or location b_A in MED curve (Figure 5). Thus, by adding half of a_d , to b_A, the offset of T-wave can be determined.

$$b_{offset} = \frac{a_d}{2} + b_A \qquad (9)$$

This special point in the rescaled MED curve after which MED value rises is called 'rising point'. The MED curve before and after rising points (A & B as shown above) is not smooth and is dental instead. This is because of discretized scales practically. Rising points, e.g. point A & B, correspond to the cross point of two consecutive rescaled CWT, $T(a_d, b)$ and $T(a_d + \gamma, b)$, where γ is the scale difference.

If we model ECG waves, e.g. T wave as single frequency waves, the relative location, b_{rel} of rising point can be obtained by solving Equation 10.

$$\begin{aligned}&\beta\gamma\left(2b_{rel} - a_d/\alpha\right) + 4\gamma\sin\left(\beta b_{rel}\right)\\&-2\left(a_d+\gamma\right)\sin\left(\beta\left(b_{rel}-0.5a_d\right)\right)\\&+2a_d\sin\left(\beta\left(b_{rel}-0.5a_d-0.5\gamma\right)\right)=0\end{aligned} \qquad (10)$$

$$\&\ \ \beta = \frac{2\pi\gamma}{a_d}$$

Where, α is the coefficient relates scale to frequency (Equation 11).

$$\begin{cases} a_d = \alpha \cdot D_d \\ D_d = \dfrac{1}{f} \end{cases} \qquad \&\ \ \alpha = 0.742 \qquad (11)$$

By searching in the T-wave vicinity, first we detect rising point in MED curve. Then T-wave offset can be determined by knowing the absolute location of rising point in practical signal, b_{abs} (Equation 12).

$$b_{offset} = b_{abs} - b_{rel} + \frac{a_d}{2\alpha} \qquad (12)$$

The same procedure can be carried out to determine QRS complex onset (Equation 12). It should be noted that QRS complex dominant scale evaluated by Equation 2 is equal to the one read from MED curve.

$$b_{onset} = b_{abs} + b_{rel} - \frac{a_d}{2\alpha} \qquad (13)$$

5. Results and Conclusion

In this paper, the task of QT interval estimation based on CWT and energy analysis is carried out.

Based on proposed mathematical relations, using the concepts of local search interval and dominant rescaled wavelet coefficients, QRS complexes are evaluated with the sensitivity about 99% and using concept of minimum variance deviation of modeled T-wave and denoised ECG signal difference, T-wave domain evaluated with the sensitivity about 97%.

We evaluated the algorithm on the PTB database. The proposed multiscale approach is achieved about 53.7 ms of RMS error. The preliminary results are sent to PhysioNet/Computers in Cardiology Challenge 2006. The algorithm is semi-automated because at the first step the dominant scale is calculated by human.

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