

Reliable Automated QT Interval Measurement for Clinical Evaluation

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Abstract

The aim of this study was to develop a reliable automated method of QT interval measurement for ECG signals, and to participate the PhysioNet/Computers in Cardiology Challenge 2006. A scheme based on Kalman filter was proposed to conduct beat segmentation and searching of the first representative beat from ECG waveform, and a wavelet based algorithm was used to detect the onset of QRS complex and the offset of T wave which yield the measurement of QT interval.

Our preliminary QT measurement results have been submitted to CinC for performance evaluation and further improvement to the algorithms and system is being carried out.

1. Introduction

The QT interval represents the time required for completion of both ventricular depolarization and repolarization and has been a parameter of particular interest [1]. This clinical parameter can be derived from the surface electrocardiogram (ECG), its measurement requires the identification of the start of the QRS complex and the end of the T wave. Accurate measurement is important as QT prolongation is associated with the risk of ventricular tachyarrhythmia and of sudden cardiac death [2].

In comparison with manual methods, automated QT interval measurements offer advantages in terms of absolute repeatability of measurements, immunity from errors related to observer fatigue, lapses of attention, and transcription, as well as efficiency and cost considerations that permit either more extensive and rigorous testing for the same cost as manual methods, or more rapid testing at lower cost. Therefore the 2006 Computers in Cardiology Challenge raised this topic to develop reliable automated methods of QT interval measurement for ECG signals. The data used for this year's challenge are the 549 recordings of the PTB Diagnostic ECG Database [3].

2. Methods

We addressed two difficulties for this challenge: one is

to accurately detect the onset of QRS complex and offset of T wave, the other is to properly select the first representative beat for QT measurement. As the golden standard is calculated as the median values of all valid manually measured entries, how to ensure our first representative beat selection follow the majority is the key issue for this challenge.

In our approach, the ECG signals are first processed to select the First Representative Beat (FRB) for QT measurement. Then the FRB positions and original ECG signal were sent to next module, where a wavelet based algorithm was used for QRS detection and QRS complex onset and T wave offset detection.

2.1. First Representative Beat Selection

Representative beat refers to the second beat in three consecutive typical beats, which is commonly used as an indicator of a person's cardio status. The strategy of locating representative beats is based on Kalman filter (KF) and is depicted as a flowchart in Figure 1.

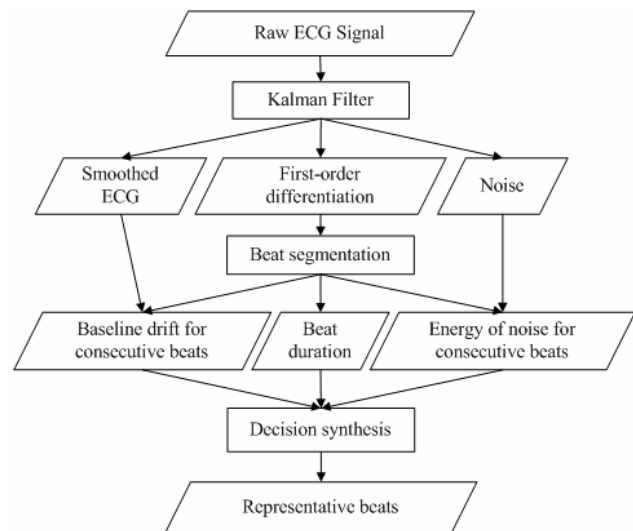


Figure 1. Work flow for locating representative beats.

The raw ECG signal, which is contaminated by baseline drift and noise, is first put through a KF. The KF

has two system variables $[x \ y]^T$, where x is the actual beat amplitude and y is the first-order differentiation (velocity) of x . Constant-velocity model is employed by the KF to track the ECG signal. Mathematically,

$$\begin{bmatrix} x_{t+1} \\ y_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_t \\ y_t \end{bmatrix} + \begin{bmatrix} Q_x \\ Q_y \end{bmatrix} \quad (1)$$

where the subscripts $t+1$ and t denote time marks, Q_x and Q_y are Gaussian noise of the system variables. The measurement function of the KF takes the form of (2).

$$z_t = [1 \ 0] \begin{bmatrix} x_t \\ y_t \end{bmatrix} + R \quad (2)$$

where z_t is the reading of the original ECG at time t and R is the measurement noise, which is also assumed Gaussian. The raw ECG is smoothed by such a KF using the standard KF recursion [4]. The outputs of the KF include smoothed ECG and first-order differentiation, which are depicted as waveforms in Figure 2(b) and (c), respectively. The noise of the ECG is defined as the difference between the raw ECG and the smoothed ECG, which is comprised of two parts: one is the system noise of the KF, the other is the measurement noise. The noise of the ECG is depicted in Figure 2(d).

In QRS complex, there are usually sharp changes in ECG waveform. When reflected on its first-order differentiation (y -waveform), there are prominent upward or downward surges as depicted in Figure 2(c). The sudden changes in y -waveform are sharper than those in the original ECG signal and they are not affected by the baseline wander. As a result, the y -waveform is used as the criteria for segmenting heart beats. By selecting a proper threshold, the steep slope, which corresponds to a QR segment, is detected by searching the first y value exceeding the threshold within short interval. The segmented beats are manifested in Figure 2(b) and (c). Given the beginning and end position of each beat, duration (length), mean value, and the energy (variance) of noise for each beat are computed at ease. Representative beats should have the following characteristics in common:

- 1) Its duration should be close to those of the majority.
- 2) Its mean value does not differ much from those of its neighboring beats, which means that the comparative baseline drift for these consecutive beats is not great.
- 3) The energy of noise of the target beat and its neighboring beats should be small as well.

In the decision synthesis module, these quantities are computed for each beat and compared with one another, typical beats are the top 10-20% that best meet these requirements. It should note that for the proposed scheme, a beat usually begins with QR slope (sometimes RS slope when QRS complex is negative) rather than the standard P onset. As a result, 4 consecutive typical beats are searched in our experiments, and the P onset of the true

representative beat should be within the second typical beat and the T offset lies in the third typical beat detected. For subsequent QT interval measurement, the Q wave is therefore searched from the beginning of the second typical beat and P wave searched within the third typical beat.

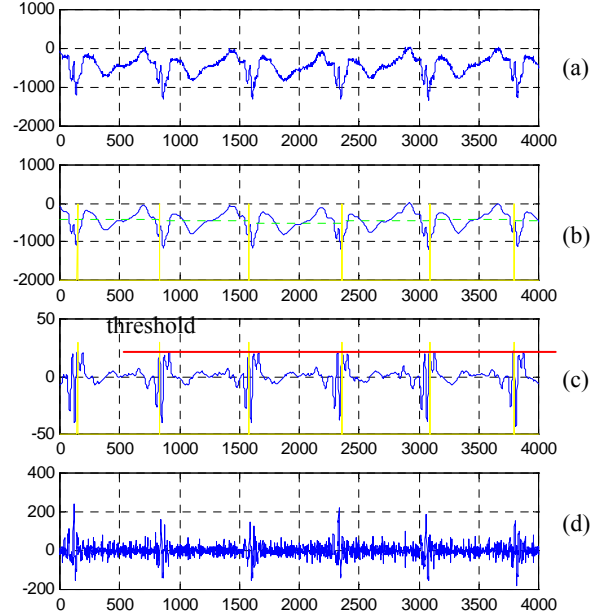


Figure 2. (a) Original ECG signal. (b) Smoothed ECG signal, mean value (dotted) and beat segmentation marker (light vertical lines). (c) First-order differentiation and the threshold for segmenting beats. (d) Noise of the ECG.

2.2. QT interval measurement

2.2.1. Wavelet transform

The wavelet transform (WT) of a function, f , with respect to a given mother wavelet, Ψ , is defined as,

$$w_s f(x) = f * \psi_s(x) = \frac{1}{S} \int_{-\infty}^{\infty} f(t) \Psi\left(\frac{x-t}{s}\right) dt \quad (3)$$

where w_s is the WT operator and s is the scale factor. Let $s=2^i$ ($i \in \mathbb{Z}$, and \mathbb{Z} denotes the integral set), then the WT is called dyadic WT. The dyadic WT can be calculated as:

$$S_{2^i} f(n) = \sum_{k \in \mathbb{Z}} h_k S_{2^{i-1}} f(n - 2^{i-1} k) \quad (4)$$

$$W_{2^i} f(n) = \sum_{k \in \mathbb{Z}} g_k S_{2^{i-1}} f(n - 2^{i-1} k) \quad (5)$$

where S_2^i is a smoothing operator, and W_2^i is the WT of digital signal $f(n)$. On the other hand, h_k and g_k are the coefficients of the corresponding low pass and high pass filters.

The close relationship between perfectly reconstructing filter banks and dyadic wavelets leads to computational efficiency. In this method the wavelet transform is implemented with a series of cascaded low-pass and high-pass filters following the approach of Mallat algorithm [5]. And to keep the time-invariance and the temporal resolution at different scales, we applied the *algorithme a trous* [6] to keep same sampling rate in all scales.

2.2.2. QRS and T wave detection

By observing the different scale of wavelet transform, it is clear that most of the energy of the ECG signal lies within the scales 2^1 to 2^5 . For scales higher than 2^4 , the energy of the QRS is very low. The P and T waves have significant components at scale 2^5 although the influence of baseline wandering is important at this scale.

Using the information of local maxima, minima and zero crossings at different scales, the algorithm identifies the significant points in the following steps: 1) detection of QRS complexes; 2) Determination of the QRS complex onset; 3) T wave detection and delineation. The flow chart of the algorithm is shown in Figure 3.

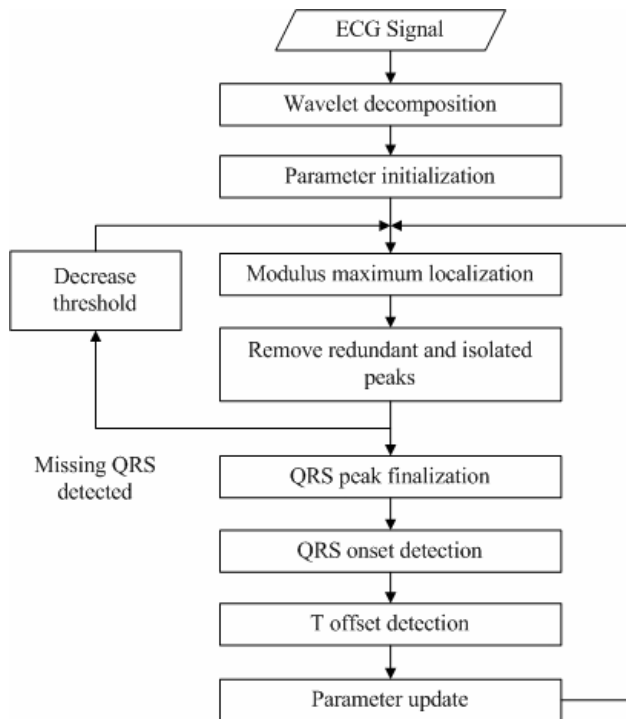


Figure 3. Flow chart for wavelet based QT measurement.

QRS Detection

Local modulus maxima are first searched at larger scales (i.e., 2^4) and then at finer scales (i.e., 2^3 , 2^2 , and 2^1). This strategy reduces the effect of high-frequency noise, which presents more in the lower scales, and there are a smaller number of modulus maxima in larger scales as well. Following this procedure, appropriate thresholds are applied to modulus maxima at the large scale to detect the modulus maxima corresponding to the QRS complex. After rejecting all isolated and redundant maximum lines, the zero crossing of the WT at scale between a positive maximum-negative minimum pair is marked as a QRS. Other protection measures are taken, like a refractory period or back-searching with lowered thresholds if a significant time has elapsed without detecting any QRS.

QRS onset detection

Normally the onset of the QRS complex contains the high-frequency components, which are detected at finer scales, here we use 2^2 . The onset is the beginning of the first modulus maxima pair.

T-offset detection

The process for T wave detection and delineation is given as follows: first of all, we define a search window for each beat, relative to the QRS position and depending on a recursively computed RR interval. Within this window, we look for local maxima. If two of them exceed the threshold Th_T , a T wave is considered to be present. In this case, the local maxima of WT with amplitude greater than some threshold λ_T are considered as significant slopes of the wave, and the zero crossings between them as the wave peaks. And the offset of T wave is the ending of the maximum module pair.

One original ECG signal with marker on QRS peak, QRS onset, T offset and corresponding wavelet transform are shown in Figure 4.

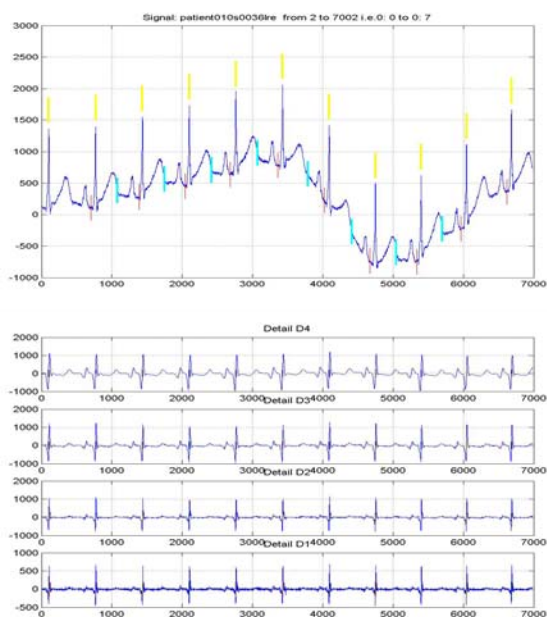


Figure 4. (a) ECG signal with markers on QRS peak, QRS onset and T offset. (b) Wavelet transform at different scales.

3. Results

The data to be used for this year's challenge are the 549 recordings of the PTB Diagnostic ECG Database [3], which was contributed to PhysioNet in September 2004 by its creators Michael Oeff, Hans Koch, Ralf Bousseljot, and Dieter Kreisler of the Physikalisch-Technische Bundesanstalt in Berlin. Each of these recordings contains 15 simultaneously recorded signals: the conventional 12 leads and the 3 Frank (XYZ) leads. Each of these is digitized at 1000 samples per second, with 16 bit resolution over a range of ± 16.384 mV. The records come from 294 subjects (each represented by one to five records) with a broad range of ages and diagnoses. About 20% of the subjects are healthy controls. A detailed clinical summary accompanies each record. The records are typically about two minutes in length, with a small number of shorter records (none less than 30 seconds) [8].

The KF based strategy has been applied to the 549 ECG samples mentioned above with 528 of them being correctly segmented into individual beats. The first three representative beats are then searched using the automated method presented in Section 2.1. Comparison is made against manual annotation results provided by another group of our team and above 60% match is achieved.

We submitted our preliminary QT measurement result to 2006 PhysioNet/Computers in Cardiology Challenge

for performance evaluation. Our latest score is 48.56 in division 2. Better performance will be achieved by further tuning the parameters.

4. Discussion and conclusions

A Kalman filter based approach was proposed for locating the first representative beat for QT measurement. By studying the duration, baseline wandering and noise level of the segmented beats, representative beats are automatically chosen and the results demonstrate good agreement with manually annotated ones.

A wavelet based algorithm was used to detect the onset of QRS complex and offset of T wave which gives the measurement of QT interval.

Our preliminary experimental results proved the effectiveness of the proposed approach and further improvement is being carried out to achieve better performance.

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