

A QT Interval Detection Algorithm Based on ECG Curve Length Transform

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Abstract

We present an algorithm that automatically computes the QT interval duration from body surface electrocardiograms (ECGs). The algorithm consists of three processing steps: (1) PQ junction detection, (2) optimal lead selection, and (3) T-wave end detection. A previously developed algorithm for QRS detection was employed to detect the onset of each QRS complex, which was taken to be the PQ junction time. In the lead selection step, the ECG lead with the largest T-wave was automatically picked by the algorithm. For the T-wave end detection, the ECG signal in the estimated T-wave portion was transformed by means of an ECG curve length transform (LT); the T-wave end was determined using the resultant LT signal. The algorithm was applied to the first 30 seconds of 532 records in the PTB Diagnostic ECG Database. A score of 29.66 was achieved, which represents the RMS difference between the reference QT intervals and the algorithm's results.

1. Introduction

QT interval measurements from electrocardiograms (ECGs) are routinely used in clinical medicine. These measurements are usually done by expert readers using calipers on paper or e-calipers on computer screens. An automated methodology, if sufficiently accurate, is highly desirable. Although there is a rich literature documenting a wide variety of approaches to the problem [1-4], the clinical community and regulatory agencies are so far unconvinced of the reliability of automated QT interval measurements.

With the work presented in this article we respond to the 2006 PhysioNet / Computers in Cardiology Challenge for QT interval measurements from body surface ECGs [5]. Our purpose is to pursue an accurate and reliable approach for fully automated QT interval detection.

We propose a QT interval detection algorithm based

on a curve length transform of the ECG signal. Our approach has the following advantages: a) it is insensitive to morphological variations of QRS complexes and T-waves; b) it is insensitive to ECG baseline wandering; and c) it is computational efficient.

2. Materials and methods

2.1. Electrocardiogram data

The data used in the challenge are the 549 recordings of the PTB Diagnostic ECG Database [6]. The recordings come from 294 subjects representing a broad range of ages and clinical pathologies. About 20% of the subjects are healthy controls. Each of these recordings contains 15 simultaneously recorded ECG signals: the conventional 12 leads and the 3 Frank (XYZ) leads. The signals are digitized at 1000 samples per second and have an amplitude resolution of 16 bits, spanning the range of ± 16.384 mV. The records are typically about two minutes in length, with a small number of shorter records (none less than 30 seconds).

We down-sampled the first 30 s of each ECG signal of the original 549 records from 1000 Hz to 250 Hz, using the open-source software utility *xform* available from PhysioNet [7]. (The reason for down-sampling the original high resolution data is in order to directly employ a previously developed QRS onset detection algorithm that was optimized on ECG signals sampled at 250 Hz.) The amplitude resolution was kept unchanged.

2.2. The algorithm

The algorithm consists of three components: 1) PQ junction detection, 2) automatic lead selection, and 3) T-wave end detection.

2.2.1. QRS onset detection

Since the PQ junction time is equivalent to QRS onset

time, the PQ junction detection was treated as QRS onset detection in this study. QRS onset detection is performed with a previously developed QRS onset and duration detection algorithm [8]. This algorithm was applied to lead II of each record.

2.2.2. Lead selection

Before detecting the end of the T-wave, a lead selection process is performed in order to find the optimal lead, in terms of T-wave prominence, for T-wave end detection.

For each of the 15 leads, the P-QRS portion of each beat in the first 30 seconds was erased and the backward length transform was applied the same way as described in 2.1.3. The maximum $L(n)$ value in each beat cycle was taken and averaged over all the beats. The leads were ranked by the average maximum $L(n)$ value. The top ranked lead was selected as the lead for T-wave end detection.

2.2.3. T-wave end detection

The T-wave end detection algorithm consists of four basic steps, as shown in Figure 1. First, for a chosen ECG lead, a low-pass filter is applied to the ECG signal, $x(n)$, resulting in the filtered signal, $y(n)$. Second, according to the QRS onset produced by the QRS onset/duration detection algorithm, the filtered ECG signal in the estimated portion of P-wave and QRS complex is replaced with the last sample value prior to the P-QRS portion resulting in the signal $y'(n)$. Third, a backward ECG curve length transform signal, $L(n)$, was calculated from the P-QRS portion backward to the prior T-wave. Finally, T-wave end detection was performed using the $L(n)$ signal.

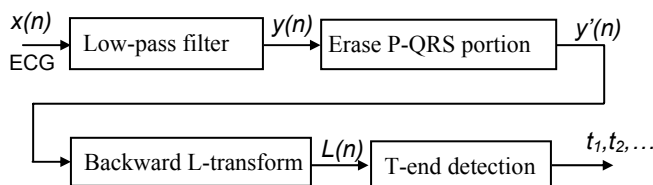


Fig. 1: Diagram of the T-wave end detection algorithm.

A second-order recursive low-pass filter [9] was employed. The difference equation is

$$y(n) = 2y(n-1) - y(n-2) + x(n) - 2x(n-5) + x(n-10) \quad (1)$$

The 3dB cut-off frequency for this filter is about 16 Hz for an ECG signal sampled at 250 Hz; the gain is 25 at 0 Hz and the phase shift is 20 ms (or 5 samples at 250 Hz).

For each beat, we define the P-QRS portion of the

cardiac beat as extending 160 ms prior to and 160 ms after the QRS onset time.

In the second processing step, this portion of the signal was replaced with the last sample value prior to the estimated P-QRS portion.

$$y'(i) = \begin{cases} y(q_k - 40), & q_k - 40 < i \leq q_k + 40 \\ y(i), & \text{otherwise} \end{cases} \quad (2)$$

where, $y(i)$ is the filtered ECG signal, $y'(i)$ is the signal with the estimated P-QRS portion replaced, q_k is the QRS onset time for each beat.

The curve length transform used in the algorithm is defined as:

$$LT(w, i) = \sum_{k=i}^{i+w} \sqrt{\Delta t^2 + \Delta y_k^2} = \sum_{k=i}^{i+w} \sqrt{C + \Delta y_k^2} \quad (3)$$

where $\Delta y_k = y_k - y_{k-1}$ and $0 < i \leq N-w$, N is the total number of the sample points and $w \ll N$. Δt is the sampling period and therefore a constant, $C = \Delta t^2$. However, it can also be considered a non-linear scaling factor [8]. The window size, w , was empirically chosen as 160 ms (40 samples); C was chosen as its original value, 16 ms^2 .

The backward length transformed signal $L(n)$ was calculated from the (replaced) P-QRS portion backward to the T-wave portion. The pseudo-code (in the C programming language) for processing one beat is as follows:

$$\begin{aligned} &\text{for } (i = q_k - 40, i > q_{k-1}, i--) \{ \\ &\quad L(i) = LT(40, i) - L_0; \\ &\} \end{aligned} \quad (4)$$

where q_k and q_{k-1} are the QRS onset points for the current beat and previous beats, respectively; $LT(40, i)$ is defined in (3); and $L_0 = w\sqrt{C}$, which is the horizontal line length value in the window.

Figure 2 shows the relationship between the backward length transform signal $L(n)$ and the T-wave signal $y'(n)$. The signal $L(n)$ deviates from zero as it sweeps past the T-wave in a backward fashion. This is because the T-wave portion has a longer curve length in a given processing window than a straight line. With a suitable criterion, the end of the T-wave can be determined by processing the signal $L(n)$. The curve length transform helps avoid baseline wandering and can easily handle positive, negative, and/or biphasic T-waves.

The final task involved the reliable detection of the onset point, from a time-reversed order, of the $L(n)$ signal. A tilted signal minimum search technique was employed in judging the onset of the $L(n)$ signal. As shown in Figure 3, for each beat, a line was calculated extending from the peak of the $L(n)$ signal to the zero level at the following

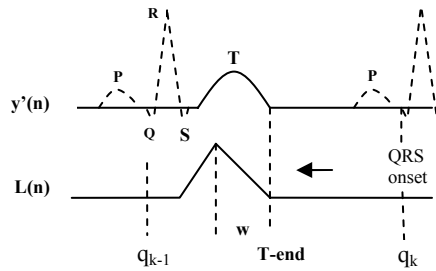


Fig 2: Relationship between the backward curve length transform signal $L(n)$ and the T-wave $y'(n)$.

QRS onset point, q_k . Along the $L(n)$ signal from the peak point to point at q_k , the distance between the signal point and the linear line was calculated, and the time point associated with the maximum distance was taken as the $L(n)$ backward onset time which corresponds to the T-wave end. This maximum distance search process can be viewed as a tilted signal minimum search. If we tilt the signal such that the calculated line is horizontal, the minimum of the signal has the maximum distance to the line.

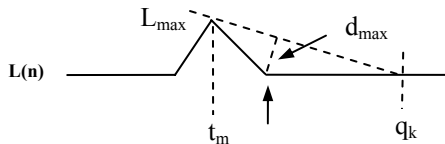


Fig. 3: T-wave end detection (see text for details).

As an additional quality control procedure, a reliability flag (RF), was defined for each beat to indicate whether the T-wave end detection for this beat is reliable or not. The RF has a binary value of 0 or 1 for unreliable or reliable, respectively. For each beat, if the T-wave end determined by this algorithm is too short (less than 250 ms) or too long (larger than 550 ms) from the prior QRS onset, the corresponding RF is set to 0; otherwise its value is set to 1. This was based on the fact that QT intervals are rarely shorter than 250 ms or longer than 550 ms.

3. Results

Figure 4 shows an example of the results from the automated lead selection process. Leads V3, V4 and V2 were determined by the algorithm to be the top 3 leads most suitable for T-wave end detection. The 15 leads of ECG signals of the same record are shown in Figure 5. As can be seen, lead II has small T-waves and might not be suitable for T-wave end detection.

Figure 6 shows an example of the algorithm-produced



Fig. 4: Example of the lead selection: V3, V4 and V2 were ranked the top leads most suitable for T-end detection.

PQ junction and T-wave end labels, along with the intermediate signals that facilitated T-wave end detection. The top trace in Figure 6 is the original ECG of the selected lead, the middle trace is the low-pass filtered signal with the P-QRS portion replaced (starting from the second beat), and the bottom trace is the backward length-transformed signal. Labels N and T are the PQ junction time and the calculated end of the T-wave, respectively.

Out of the total of 549 records in the database, 17 had a reliability flag value of zero for the second beat, meaning the T-wave ends were not reliably detected. Those 17 records were excluded from further analysis. The PQ junction time and the T-wave end from the second beat of each of the remaining 532 records were submitted to the PhysioNet Challenge 2006 for scoring. A score of 29.66 was achieved. The score for each entry is calculated as the RMS difference between the reference QT intervals and the corresponding QT intervals listed in the entry.

4. Conclusion and discussion

A QT interval detection algorithm based on an ECG curve length transform has been developed. It consists of a previously published QRS onset detection algorithm, an automated lead selection step, and a new T-wave end detection algorithm. The proposed algorithm has several advantages: a) it has a clear physiological and mathematical basis; b) it easily handles positive, negative, and/or biphasic T-waves; c) it is insensitive to baseline wandering; d) the determination of the T-wave end does not need any threshold; and e) it is computationally efficient.

The lead selection process is important as the T-wave end can only be detected reliably in the ECG lead with discernable T-waves. However, QT intervals measurable from different leads are generally different because the myocardial repolarization activity is generally projected differently on different leads. The lead determined by the

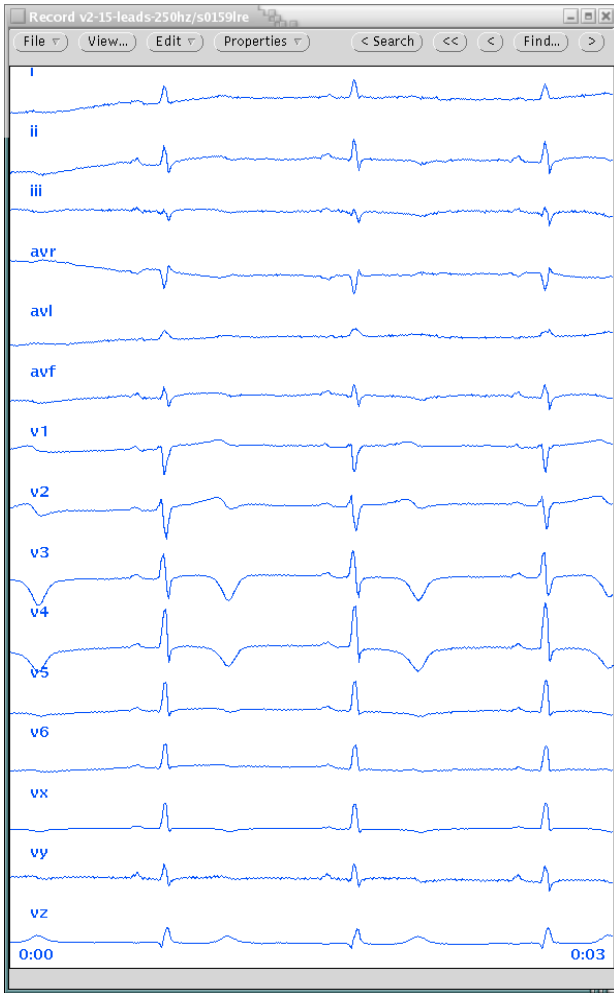


Fig. 5: Example of the original 15 leads of the ECG record.

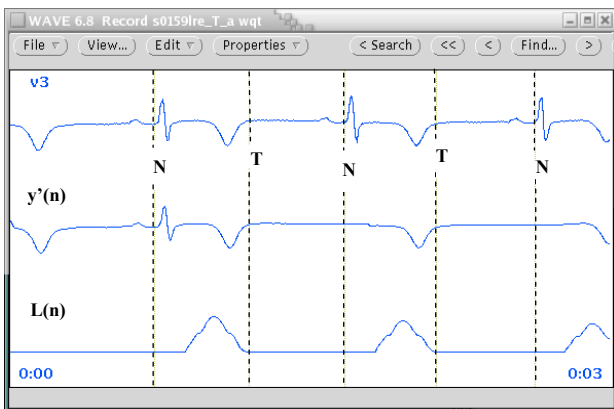


Fig. 6: Example of the QRS onset and T-wave end detection process.

algorithm's automated lead selection process is most often one of the V leads rather than Lead II even if the latter contains visible T-waves. As the Challenge preferred Lead II for QT interval measurement, one of

the error sources might be due to this lead difference. Processing multiple leads for T-wave end detection may be necessary in order to reduce the error caused by the lead difference.

There could also be systematic bias between the algorithm's results and the reference. Once the reference becomes published, such constant bias can be identified and compensated for.

Beat classification prior to performing QT interval measurements may improve the performance by rejecting ectopic beats.

Future work includes fine-tuning the algorithm with known QT interval reference datasets and multiple lead processing toward more consistent QT interval detection.

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References

- [1] Laguna P, Jané R, Caminal P. Automatic detection of wave boundaries in multilead ECG signals: validation with the CSE database. *Computers and Biomedical Research*, 1994 Feb; 27(1):45-60.
- [2] Li C, Zheng C, and Tai C. Detection of ECG characteristic points using wavelet transforms. *IEEE TBME* 1995 Jan; 42(1):21-28
- [3] Martinez JP, Almeida R, Olmos S, Rocha, AP, and Laguna P. A wavelet-based ECG delineator: evaluation on standard databases. *IEEE TBME* 2004 Apr; 51(4):579-581.
- [4] Zhang Q, Illanes Manriquez A, Medigue C, Papelier Y, and Sorine M. Robust and efficient location of T-wave ends in electrocardiogram. *Computers in Cardiology* 2005; 32:711-714.
- [5] Moody GB, Koch H, Steinhoff U. The PhysioNet/Computers in Cardiology Challenge 2006: QT Interval Measurement. *Computers in Cardiology* 2006; 33 [in this volume].
- [6] <http://www.physionet.org/physiobank/database/ptbdb/>
- [7] <http://www.physionet.org/physiotools/wfdb/app/xform.c>
- [8] Zong W, Moody GB, Jiang D. A robust open-source algorithm to detect onset and duration of QRS complexes. *Computers in Cardiology* 2003; 30:737-740.
- [9] Lynn PA. Online digital filter for biological signals: some fast designs for a small computer. *Med Biol Eng Comput* 1977; 15:534-540.

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