AUTOMATIC DETECTION OF ECG WAVE BOUNDARIES USING EMPIRICAL MODE DECOMPOSITION

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ABSTRACT

Automatic detection of the boundaries of ECG characteristic waves with a reasonable accuracy has been a difficult task. This paper presents an algorithm based on empirical mode decomposition (EMD) for automatically locating the waveform boundaries (the onsets and offsets of P, QRS, and T waves) in generalized single lead ECG signals. First, the R peak of each beat is detected from the first three intrinsic mode functions (IMFs) of the EMD analysis of the filtered ECG signal. Next, the onset and offset of each QRS complex are located. The P wave and T wave, relative to each QRS complex, are then identified using a set of higher order IMFs. Our algorithm is tested using the QT database (reference annotated database) and the MIT-BIH arrhythmia database. Examples of detection of the fiducial points and a comparison with the threshold-based detector are presented for the assessment of performance of the algorithm.

Index Terms— ECG characteristic waves, empirical mode decomposition, intrinsic mode function.

1. INTRODUCTION

The determination of the primary fiducial points (onset and offset of QRS complex, P and T waves) of a heart cycle is the most important step of quantitative ECG analysis. It is additionally complicated by the usual presence of noise, powerline interference, electromyogram artefacts, baseline fluctuation in the original signal and by irregularity of the waveforms. Many detection methods have been developed to the automatic detection of the ECG wave boundaries (fiducial points) [1]-[3]. Most of these methods are based on filtering or adaptive thresholding, which exhibit limitation in real life applications. Frequency variations in the characteristic waves adversely affect the performance of filtering-based approaches. The thresholding techniques [1] are highly noise sensitive, and the multiscale morphological derivative (MMD) method [3], which is limited to lead II, cannot always detect the Q and S waves accurately.

In this paper, we propose a robust method for the detection of ECG characteristic wave boundaries using empirical mode decomposition (EMD). The EMD is a powerful tool for analysing nonlinear and non-stationary data. The aim of EMD is to decompose the signal into a sum of intrinsic mode functions (IMFs) [4]. An IMF represents the oscillatory mode embedded in the data. The reason behind using the EMD lies in the fact that lower order IMFs capture fast oscillation modes while higher order IMFs typically represent slow oscillation modes. The lower order IMFs of ECG can be used to distinguish the QRS complex in the ECG signal from high P or T waves, noise, and baseline drift. A smooth ECG signal can be obtained from the higher order IMFs from which the P and T waves can be detected.

2. DETECTION OF ECG WAVE BOUNDAIES

The proposed EMD based detector is a single lead detection method which works not only for ECG lead II, but also for other leads satisfactorily. The detailed procedure for ECG characteristic wave detection using EMD is described in the following.

2.1. Signal preprocessing

The ECG signal is preprocessed by an FIR filter of order 3 to reduce some high frequency noise like interspersions and muscle noise keeping the sharpness of the QRS complex intact. The FIR filter coefficients are chosen as $\{0.8 \;\; 0.1 \;\; 0.1\}$. After filtering in the forward direction, we reverse the filter coefficients and run the sequence back through the filter. The resulting sequence has precisely zero-phase distortion and double the filter order. Then, a drift suppression is applied to the resulting signal. This is done by a high pass filter with a cut-off frequency of 1 Hz. The filtering process is carried out in a MATLAB routine. Signal preprocessing is necessary only for the ECG signals that contain significant noise. The preprocessed ECG signal is denoted as $x(t)$.

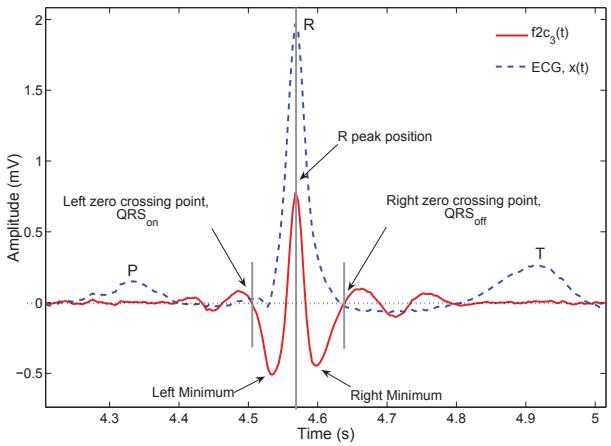

Fig. 1. Illustration of the QRS complex detection.

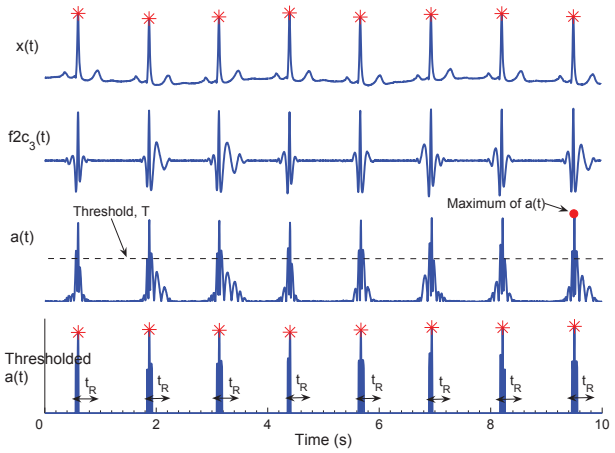

Fig. 2. Steps for the R-peak detection.

2.2. Decomposing ECG into IMFs

Now, the EMD is applied on $x(t)$ and the IMFs are obtained to locate the fiducial points in the ECG signal. The EMD of $x(t)$ is given by [4],

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{1}$$

where $c_i(t)$ is the ith IMF and $r_n(t)$ is the residue.

2.3. R peak detection

Since the R wave is the sharpest component in the ECG signal, it is captured by the lower order IMFs which also contain high frequency noise. Past analysis using the EMD of clean and noisy ECG indicates that the QRS complex is associated with oscillatory patterns typically presented in the first three IMFs [5]. In our analysis, we have also found similar results. We denote the sum of first three IMFs as fine to coarse three, $f2c_3(t)$ given by

$$f2c_3(t) = \sum_{i=1}^{3} c_i(t) \tag{2}$$

The oscillations associated with QRS complex in $f2c_3(t)$ are much larger than those due to noise. Fig. 1 shows $f2c_3(t)$ with $x(t)$ for a single ECG beat. It reveals that the R-peak in the ECG signal is detected by the peak of $f2c_3(t)$. Therefore, the R-peak detection comprises the following steps which are also illustrated in Fig. 2 for a series of ECG beats:

(i) Sum the first three IMFs to get $f2c_3(t)$ and take its absolute value as $a(t)$.

(ii) Retain the amplitudes of $a(t)$ larger than a threshold, T, where T is statistically selected to be half of the maximum value of $a(t)$ and make others zero. This eliminates the noise.

(iii) Find the position of the maximum of a segment of time duration t_R starting from the first non zero value of $a(t)$ (Fig. 2). This is the first R-peak position. Similarly, find all other R-peak positions until the end of $a(t)$ is reached.

According to the width of QRS complex which is normally 100 ms with variation of $\pm$20 ms [6], we select t_R to be about 200 ms. We have considered the absolute value of $f2c_3(t)$ since R-wave, and thus $f2c_3(t)$, give a negative peak in some ECG leads. After finding the R-peak position, t_o, we can find whether the peak is positive or negative from the value of $f2c_3(t_o)$. If $f2c_3(t_o)$ is positive, then the R-peak is positive since the base of $f2c_3(t)$ is zero.

2.4. QRS onset and offset detection

The onset and offset of QRS complex are also marked using $f2c_3(t)$. Fig. 1 shows that the QRS complex is bounded by the two zero crossing points of $f2c_3(t)$. For positive (negative) R-peak, these two points correspond to the first two zero crossing points beyond the left minimum (maximum) and the right minimum (maximum) of the R-wave, as shown in Fig. 1. To detect the minima (maxima), we find the minimum (maximum) of a segment of $f2c_3(t)$ from each side of the R-peak, with a time interval of 0.1 times the RR interval (calculated from the R-peaks) of the two beats adjacent to the segment. By considering the two minima (not always the nearest local minima), we remove false detection due to large noise and the problem of a sub-R peak for the left bundle branch block (LBBB) ECG beat.

2.5. P wave detection

Next, the P wave is searched on the left of the onset of the QRS complex. The P wave peak is obtained from $x(t)$ but the noise remaining in $x(t)$ hinders the detection of the onset and offset of P wave from $x(t)$. It is found that the onset and offset can be detected from $c2f_2(t)$ and $c2f_3(t)$, where

$$c2f_n(t) = x(t) - f2c_n(t) = x(t) - \sum_{i=1}^{n} c_i(t) \tag{3}$$

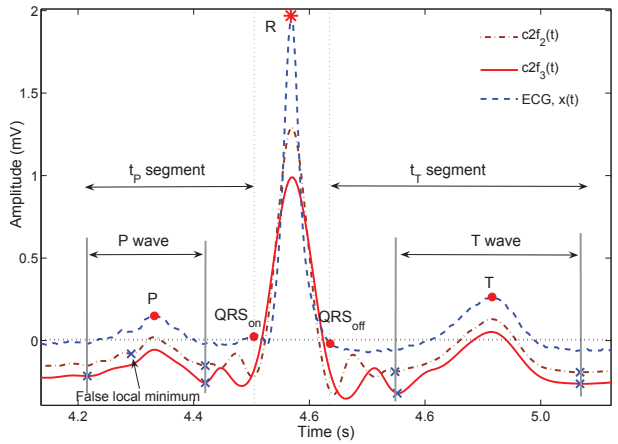

Fig. 3. Illustration of the P and T waves boundary detection.

Fig. 3 shows a typical ECG beat with the signals $c2f_2(t)$ and $c2f_3(t)$. A close examination on Fig. 3 reveals that for positive P wave peak, the onset of P wave is marked by the first local minimum of $c2f_2(t)$ and $c2f_3(t)$ from the left hand side of the P wave peak, and the offset of P wave is marked by the first local minimum of $c2f_2(t)$ and $c2f_3(t)$ from the right hand side of the P wave peak. Similar phenomena is also observed for the T wave. Although only $c2f_2(t)$ could be used to determine the onsets and offsets for many ECG beats, we have considered both $c2f_2(t)$ and $c2f_3(t)$ to prevent false local minima near the P and T wave peaks due to noise. Thus the detection of P wave consists of the following steps:

(i) Take a segment of the filtered ECG signal of time duration t_P from the left of the onset of QRS complex.

(ii) Find the peak (positive or negative) of this segment. It is the P wave peak.

(iii) If the P wave peak is positive (negative), find the first local minimum (maximum) of $c2f_2(t)$ and $c2f_3(t)$ from the left hand side of the P wave peak and identify the minimum (maximum), which is further away from the P wave peak, as the onset of P wave.

(iv) Similarly, find the first local minimum (maximum) of $c2f_2(t)$ and $c2f_3(t)$ from the right hand side of the P wave peak and identify the minimum (maximum), which is further away from the P wave peak, as the offset of P wave.

Normal range of PQ/PR interval is 160 ms with a variation of ± 40 ms for a heart rate of 60 bpm [6]. Thus selection of t_P to be one third of the RR interval of the adjacent beats is a good choice. This prolonged t_P enables to detect P wave in case of AV block where there is a delay between the atrial P wave and the ventricular QRS complex.

2.6. T wave detection

The T wave is searched on the right of the offset of the QRS complex. As for the P wave, the T wave peak is obtained from $x(t)$ and the onset and offset of T wave are detected from $c2f_2(t)$ and $c2f_3(t)$ (Fig. 3). The detection steps for the T wave are similar to that for the P wave (Sec. 2.5) with the following modifications:

(i) Take a segment of the filtered ECG signal of time duration t_T from the right of the offset of QRS complex.

(ii)-(iv) Same as that given in Sec. 2.5 with the P wave replaced by the T wave.

Since the T wave width (normal range 300 ± 40 ms for 60 bpm) is larger than the P wave width, t_T is selected to be two third of the RR interval of the adjacent beats.

3. RESULTS

3.1. Data analysis

The proposed EMD based algorithm for the detection of characteristic wave boundaries in ECG signal was tested using the QT database [7] and the MIT-BIH arrhythmia database [8]. The QT database was designed for evaluation of algorithms that detect waveform boundaries in ECG. The database consists of 105 fifteen-minute excerpts of two channel Holter recordings with a sampling frequency of 250 Hz, chosen to include a variety of QRS and ST-T morphologies. The records included in the QT database were taken from existing ECG databases, including the MIT-BIH Arrhythmia Database, the MIT-BIH ST Change Database, the MIT-BIH Supraventricular Arrhythmia Database, the MIT-BIH Normal Sinus Rhythm Database, the MIT-BIH Long-Term ECG Database, the European Society of Cardiology ST-T Database, and from "sudden death" patients from BIH. The MIT-BIH arrhythmia database contains 48 two-channel records (each 30 minutes long) with a sampling frequency of 360 Hz.

More than 1000 annotated ECG beats from the QT database and 10000 normal ECG beats randomly selected from the MIT-BIH arrhythmia database were used to test the performance of the new algorithm for the detection of ECG wave boundaries.

To reduce the processing time required by EMD, we put a limit on the maximum number of iterations in the EMD MATLAB routine (for an example, 400 for a 10 s ECG signal). Moreover, because of the distortion caused by end effects of EMD, we exclude the two end beats from our evaluation.

3.2. Results on boundary detection

We present in Fig. 4 some results of the EMD based algorithm on boundary detection of ECG characteristic waves for signals of different leads. The boundaries are marked by dots.

Waveform boundaries for a minimum of 30 beats from each of 105 records in the QT database were manually annotated by cardiologists. The annotation files were taken as reference for evaluating the performance of the algorithms. The

Table 1. Performance of EMD based detection algorithm

Method	Parameter	P_{on}	P_{off}	QRS_{on}	R_{peak}	QRS_{off}	T_{on}	T_{off}
EMD	$\mu(ms)$	5.6	-7.3	2.3	0.5	-1.8	4.4	-7.6
	$\sigma(ms)$	13.3	11.7	5.2	3.9	8.9	16.6	18.1
TD	$\mu(ms)$	9.4	-6.1	-5.8	-3.3	-2.5	19.5	15.2
	$\sigma(ms)$	13.7	14.2	8.7	5.6	11.3	25.4	26.9
CSE	$\sigma_{ref}(ms)$	10.2	12.7	6.5	-	11.6	-	30.6

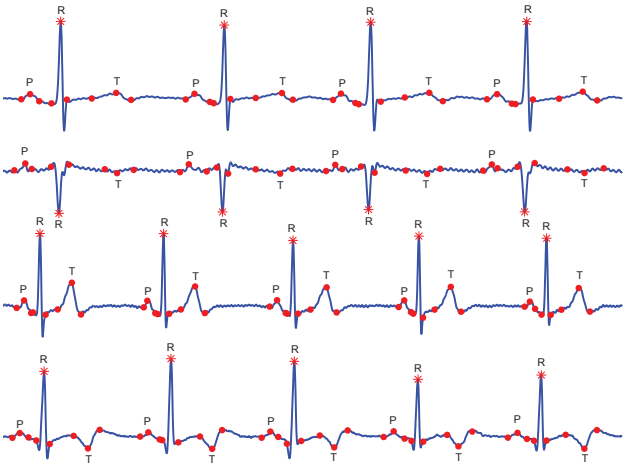

Fig. 4. Results of the characteristic wave detection in ECG signal series using EMD. The ECG signals correspond to (from top to bottom) lead MLII, V1 (record 115), V2 (record 117) and V5 (record 100) from the MIT-BIH arrythmia database.

evaluation has been carried out in terms of mean (μ) and standard deviation (σ) of the differences between the annotation results and the automated detection results. We have compared the performance of our algorithm with the threshold-based detector (TD) [7]. In Table 1, we present the statistical results for μ and σ together with the accepted tolerance for referee deviations (σ_{ref}) required by the CSE committee [9]. The EMD detector performs better than the TD method and also fulfills the CSE requirement except for the P wave onset.

The proposed EMD method works better for the QRS complex detection. Detection sensitivity of 100% are observed for the QRS complex detection. It is because the fast oscillatory QRS complex is highly detectable in the lower order IMFs irrespective of other characteristic wave amplitudes.

4. CONCLUSIONS

In this paper, we have developed a new algorithm based on the EMD for the automatic detection of ECG wave boundaries. The proposed algorithm exhibits better performance than the threshold based technique and achieves high sensitivity for the QRS complex detection. Also the measurements of the waveform boundaries are quite within the limits as required by the CSE committee. The EMD method works not only for lead II but also for other leads. Only three lower order IMFs are needed to completely identify the fiducial points in the ECG signal. Given these locations, features of clinical importance (such as the RR interval, the PQ interval, the QRS duration, the ST segment, the QT interval, and the wave amplitudes) may be measured readily.

5. REFERENCES

[1] P. Laguna, R. Jane, and P. Caminal, "Automatic detection of wave boundaries in multilead ECG signals: Validation with the CSE database," *Comput. Biomed. Resear.*, vol. 27, no. 1, pp. 45–60, February 1994.

[2] I.K. Daskalov and I.I. Christov, "Electrocardiogram signal preprocessing for automatic detection of QRS boundaries," *Med. Eng. Phys.*, vol. 21, pp. 37–44, Jan 1999.

[3] Y. Sun, K. L. Chan2, and S. M. Krishnan, "Characteristic wave detection in ECG signal using morphological transform," *BMC Car. Dis.*, vol. 5:28, Sept 2005.

[4] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and hilbert spectrum for nonlinear and nonstationary time series analysis," *Proc. R. Soc. Lond.*, vol. 454, pp. 903–995, 1998.

[5] M. B-Velasco, B. Weng, and K. E. Barner, "ECG signal denoising and baselinewander correction based on the empirical mode decomposition," *Comput. Bio. Med.*, vol. 38, pp. 1–13, 2008.

[6] G. D. Clifford, F. Azuajeand, and P. McSharry, *Advanced methods and tools for ECG data analysis*, chapter 3, pp. 61–62, Artech House, Oct 2006.

[7] P. Laguna, R. G. Mark, A. Goldberger, and G. B. Moody, "A database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG," *Comput. Cardio.*, vol. 24, pp. 673–676, 1997.

[8] The MIT-BIH Arrhythmia Database: http://www.physionet.org/physiobank/database/mitdb.

[9] The CSE Working Party, "Recomendations for measurement standards in quantitative electrocardiography," *Eur. Heart J.*, vol. 6, pp. 815–825, 2008.