A New Fitting Approach for Online Electrocardiogram Component Waves Delineation

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Abstract

A real-time capable and accurate template-based fitting approach for the detection and delineation of all the QRS-complexes, P-, and T-waves is presented. The ECG features extraction is accomplished with a very low amount of ECG signal preprocessing. The performance of our proposed algorithm is validated using ECG records from both the MIT-BIH Arrhythmia and QT standard databases. All of the ECG component waves detectors achieved very high detection rates, detecting correctly up to 3015, 3013, and 3010 QRS-complexes, P- and T-waves respectively from 3015 cardiac beats. The delineation results showed that the standard deviations of the errors are within the tolerance limits.

1. Introduction

Reliable Electrocardiogram component waves delineation is of great importance for the accuracy in ECG analysis and interpretation. It consists in the detection of the waveforms boundaries of the QRS-complex, P- and T-waves respectively. ECG signal delineation can be done manually by expert cardiologists, but such a solution is expensive and time consuming. Consequently, automated methods for ECG component waves detection and delineation have become a very active area of research in biomedical signal processing, and have evolved during the past four decades. Nevertheless, their performance has to be validated through comparisons with expert annotations, which are considered as the golden standard.

Various approaches have been adopted for ECG signal features extraction. A large variety of QRS detection algorithms is found in the literature. An extensive review is available in [1]. Different processing techniques for QRS detection show very high detection accuracy but they have not been adapted for defining the onset and offset of the QRS-complex [2], [3]. Wavelet transform based methods were used in [4], [5] for QRS detection and delineation. In [6] a modification to these methods was proposed to allow for better QRS delineation using Genetic Algorithms for threshold selection. A wavelet-based algorithm was presented in [7] for T-wave delineation by using multiscale differential operator. Timing characterization of the P- and T-waves in the ECG was developed in [8] using wavelet transform with a modified mother wavelet. Alvardo et al. [9] used different algorithms based on the continuous wavelet transform with splines to delineate the QRS and T-waves. In [10] an optimized version of the MOBD algorithm [11] was applied to delineate the QRS-complex, whereas a different method based on the Joeng algorithm [12] was used for the P- and T-waves delineation. However, all of the afore mentioned works deal with the delineation of a subset of the ECG component waves, generally the QRS-complex, or only with their detection, or use different approaches to delineate all of them resulting in a larger complexity.

The concept of a multi-component based approach was introduced in [13] to delineate all of the ECG component waves. However, this approach has poor detection rates for T-waves and especially for P-waves compared with the detection rate of the QRS-complex. Recently, a method based on adaptive quantized threshold detection was applied to the delineation of all the QRS-complex, P- and T-waves in 12-lead ECG [14]. The drawback of this method is the big amount of pre-processing for ECG signal filtering. Filtering of the raw ECG signal for noise removal and baseline drift removal is prerequisite in this method, due to the inclusion of slope and threshold decisions.

We present in this work a new method for the detection and delineation of all the important ECG waves: the QRS-complexes, the P- and T-waves. This method relies on our recently published template-based modelling approach [15], which is originally used only for ECG signal compression. Our real-time capable and accurate algorithm with a low amount of ECG signal pre-processing uses three parameterized templates for the three different ECG component waves detectors. By fitting the appropriate template to the corresponding signal part in estimated time windows and using a nonlinear least squares optimization procedure, four parameters for height, width, location in time and vertical dislocation are determined. Without further performing of gradient searches, ECG component waves onsets, peaks and offsets are extracted directly and a continuous improvement of the time windows estimation is carried out. The rest of the paper is organized as follows. Section 2 describes our implemented fitting method for online electrocardiogram component waves delineation. The experimental results of our method in terms of detection and delineation accuracy are presented in sections 3 and 4. Section 5 concludes the paper.

2. Methods

The motivation for the proposed approach is the need for a real-time ECG processing algorithm, which can be applied in, e.g., a Wireless Body Area Sensor Network (WBASN) environment. WBASNs have emerged as an efficient application for Tele-healthcare, providing ambulatory, continuous and real-time monitoring of vital signs. Implementation of an automated ECG signal delineation for real-time applications in such an environment requires besides accuracy and stability, low computational cost and low execution time.

Typically, ECG processing algorithms consist of three steps: preprocessing, ECG waves detection, and waves boundaries extraction. Fig. 1 depicts a flowchart for a typical ECG signal processing. The preprocessing step deals with signal artifacts filtering, baseline wandering removal, and beats averaging. With the help of a decision stage, ECG components waves are localized in the signal. After detection, the extraction of waves onsets, peaks, and offsets is performed as an independent step.

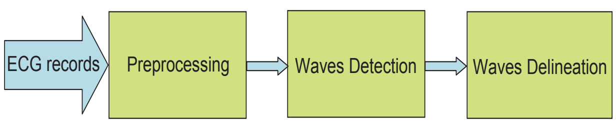

Figure 1. Flowchart of typical ECG signal features extraction

To reduce the computational load and consequently the execution time of the ECG signal processing, we developed an algorithm, which minimizes the ECG signal preprocessing, and combines the detection and delineation steps to only one step.

The proposed algorithm relies on an ECG template-based modeling [15], and contains the following stages.

In the *calibration stage*, representative templates of the QRS-complex, P- and T-waves are extracted from the subject's recorded ECG signal (see Fig. 2). For this reason, this stage is also called stamp stage, providing an identification of the subject's electrocardiogram. Tabulated time X_{-T} and amplitude Y_{-T} values of sampled data points in the different signal parts are stored as the respective digitalized templates.

It is important to mention that the template extraction

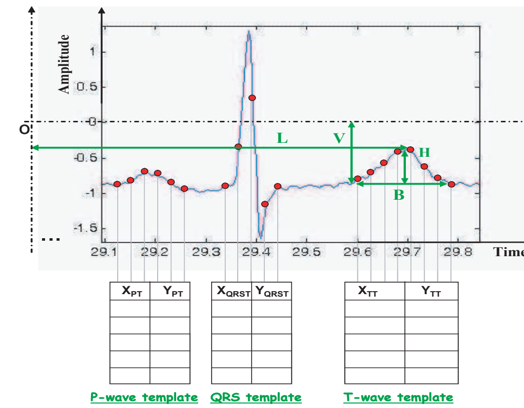

Figure 2. Parametrized tabulated templates

is only once processed for each subject. Each template is specified by a parameter set $\beta = \{H, B, L, V\}$, where H is the height, B is the broadness, L is the location in time, and V is the vertical dislocation of the baseline. Thus, the four parameters capture the changes of the ECG component wave in amplitude, width, location in time, and vertical dislocation.

The *learning stage* is required for the online execution of the algorithm. During this stage, ECG component waves are localized in a 2s recorded signal period. An initial guess of their describing parameters is assessed by means of heuristics. The appropriate template is fitted to sampled data points around the peak or trough of the respective sub-wave, and accurate parameters are consequently determined. The parameters (H, B, L, V) are performed using a nonlinear optimization procedure based on the Levenberg Marquardt algorithm [16]. The algorithm minimizes the sum of the squared errors between the sampled data and the corresponding parameterized template, so that an optimal parameter set β is determined. Time periods between the peak or trough of each sub-wave and the R-peak of the same cycle are normalized relative to the last measured RR-interval, providing an estimate of the search windows centres for the different sub-waves in the next stage.

In the *analysis stage* the detection and delineation of all the ECG sub-waves are accomplished. This stage is based on the prediction of the sub-waves positions in the signal. It also exploits the similarity characteristic of the ECG signal across its cycles. Only in the estimated search windows, sampling data points are fitted to the respective tabulated template. The initial guess of the parameter set is the one computed after fitting the same sub-wave in the previous cycle. Normalized time periods between the actual R peak and the extremum of each ECG component wave are actualized, so that the estimation of the search windows is continuously improved. The determined parameter set is controlled according to feasibility. By a calculation error, the unfeasible parameter set is rejected, and heuristics are performed in the actual signal part.

2.1. Determination of the ECG features

The four parameters obtained after fitting the respective parametrized templates to the corresponding ECG signal sections are used to determine the ECG component waves features, namely their peaks, onsets and offsets:

- peak[mV] = $[H_i * H_{iT}] + V_i$
- onset[ms] = $[Onset_{iT} * B_i] + L_i$
- offset[ms] = $[Offset_{iT} * B_i] + L_i$

where index i designates the different ECG component waves and index T denotes the template.

3. Detection results

Our detection algorithm has been first tested on approximately 3000 cycles of different ECG recordings sampled at 250 Hz from the standard annotated PhysioNet QT Database [17]. The algorithm was implemented using C code on a 1.7GHz P4 processor. Two statistical measurements were used to assess the performance, namely detection rate (DR), which gives the ratio of correctly detected waves to the total number of the same wave, and positive predictivity (+P), which is defined by, +P = (TP/(TP+FP))*100, where TP (True Positives) denotes the number of the true detected beats, and FP (False Positives) is the number of extra detections. Table 1 shows that all of the QRS complexes were correctly detected. Moreover, we had only two P-wave and 5 T-wave false detections, representing extremely low error detection rates of 0.07%, and 0.17% for the P- and T-waves respectively.

Table 1. Detection results for the proposed algorithm applied to 3015 beats from the QT database

ECG waves	TP	FP	FN	DR[%]	+P[%]
P-wave	3013	2	0	99.93	99.93
QRS	3015	0	0	100	100
T-wave	3010	5	0	99.83	99.83

The proposed detection algorithm is then compared with well-known QRS detection algorithms including Saxena [18], So [19], and MOBD [11], reported in the literature [10] as the algorithms which satisfy both the real-time and accuracy criterions the best. Two ECG recordings are selected from the MIT-BIH Arrhythmia Database. The ECG recording 100 does not contain any noise, while the recording 104 includes disturbed signals. The comparison results between our detection approach and the above mentioned algorithms are listed in table 2 in terms of +P, and sensitivity (Se), which is given by, Se = (TP/(TP+FN))*100, where FN (False Negatives) is the number of missed detections. It can be clearly seen from table 2 that our method outperforms all the three algorithms with a sensitivity of 100% for both recordings 100 and 104, and a positive predictivity of 100% and 98,7% respectively.

Table 2. Comparison results for two ECG signals

Algorithm	Signal	Se [%]	+P [%]
Saxena	100	100	97.73
	104	75.81	47.96
So	100	100	99.23
	104	92.74	79.31
MOBD	100	100	100
	104	86.29	87.7
proposed	100	**100**	**100**
	104	**100**	**98.7**

4. Delineation results

Furthermore, our algorithm is evaluated according to the ECG component waves delineation. The same dataset from the QT Database as for the detection performance evaluation was selected. The accuracy of the waveforms boundaries detection is validated through comparisons with available manually annotated beat markers provided by expert cardiologists. The mean and standard deviation of the differences between the manual and detector's wave boundary annotations were calculated. The standard deviations obtained comply with the expert tolerance limits recommended for an automated detection algorithm, as shown in table 3.

5. Conclusion

A new approach for ECG component waves detection and delineation has been presented in this work. The developed approach is based on ECG template fitting. It has the ability to not only detect all of the ECG component waves, but also to delineate all of them accurately, combining the detection and delineation steps to only one step. This reduces considerably the computational load and execution time of the algorithm (around 40μs to detect and delineate one QRS-complex on a 1.7GHz P4 processor), making it very suitable for real-time ECG analysis applications. Another big advantage of our method is the low amount of pre-processing needed to filter the ECG signal. The introduction of the vertical dislocation parameter V eliminates the need for baseline wandering removal. The method has been applied on ECG records of the MIT-BIH Arrhythmia and the standard QT databases, and validated with more than 3000 beats. The QRS detector obtained a sensitivity of Se=100%, a positive predictivity of P+=100%, and an accuracy detection rate DR= 100%. Compared to other

Table 3. ECG features accuracy following exposure to 3015 cardiac cycles

ECG features	P-onset	P-offset	QRS-onset	QRS-offset	T-offset
me[ms]	-2.59	7.17	-0.93	0.56	4.58
SD[ms]	7.56	9.25	6.37	5.24	13.75
Tolerance SD[ms]	**10.2**	**12.7**	**6.5**	**11.6**	**30.6**

well-known QRS detection algorithms, which are reported in the literature as the algorithms which satisfy both the real-time and accuracy criterions the best, it outperformed all of them. Both the P- and T-waves detectors have also achieved very high accuracy detection rates of 99,934% and 99,834% respectively. Finally, the delineation results showed that the standard deviations of the errors are within the tolerance limits recommended for an automated detection algorithm.

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