Optimizing the detection of characteristic waves in ECG based on exploration of processing steps combinations

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Abstract—**In this paper, algorithms for detection of characteristic waves in ECG are examined and modified. We distinguished four processing steps of detection algorithms: noise and artefacts reduction, transformations, fiducial marks selection of wave candidates, and decision rule. Several algorithms for detection of QRS, P, and T waves are explored through combinations of processing steps, in order to achieve accurate detection results. Algorithms are tested on public available ECG databases with both QRS and P and T waves annotations. We found that, depending on the database, the combination of Sun Yan's MMF or MMD methods with Elgendi's algorithm works best for QRS detection (Se = 99.77% +P = 99.72% for MMF on MIT-BIH Arrhythmia Database and Se = 99.90% +P = 99.89% for MMD on QT Database), while P and T waves were best detected using only Elgendi's algorithm (P waves: Se = 60.84% +P = 59.61%, T waves: Se = 88.79% +P = 93.55% on MIT-BIH Arrhythmia Database). Our work shows that combining the best proposed methods in literature may lead to improvements in ECG waves detection, although P and T waves detection is still less than satisfactory and warrants further research.**

Keywords— **ECG, characteristic waves, detection, algorithms, biomedical signal analysis.**

I. INTRODUCTION

Electrocardiogram (ECG) reflects electric polarization and depolarization of the heart chambers. Characteristic waves in ECG are known as P wave, QRS complex, and T wave. P wave reflects depolarization of the atria, QRS complex corresponds to the ventricular depolarization, and T wave represents ventricular repolarization, i.e. restoration of the resting membrane potential [1]. The repolarization of atria is concealed by QRS complex. Duration and amplitude of ECG waves (P, QRS, T) and segments between waves (ST segment, QT interval, PR interval) are used to indicate and detect patients' normal or abnormal heart rhythm and state of health.

Under the MULTISAB[1] project [2,3], in which the main goal is to construct a web platform capable of analyzing multiple heterogeneous biomedical time-series, we are currently investigating morphological ECG features for detection of three heart diseases: atrial fibrillation (AF), acute myocardial ischemia (AMI) and congestive heart failure (CHF), with intent to expand the work to other disorders in the future. Some of the features that are important for diagnosis of the heart diseases or which indicate that additional tests should be performed are listed below:

- **AF**: P wave absence, f waves (fibrillatory rate), QRS interval,
- **AMI**: J point amplitude (from baseline), R/S ratio, T wave amplitude, ST segment slope, QT interval variability,
- **CHF**: Q wave amplitude, PR interval, P wave amplitude, R wave amplitude, QRS duration, S wave duration, R wave duration.

For all three diseases, we also consider some heart rate variability features [4]. To extract the features, highly reliable detection of the ECG waves is necessary. QRS complex detection is far more investigated in literature than P and T waves detection, due to attainability of annotated signal databases. MIT-BIH Arrhythmia Database is widely used for testing the R peak detection algorithms. Pan and Tompkins [5] in 1985 reported high accuracy detection (> 99%) of QRS complexes with their algorithm based on filtering, derivation and adaptive thresholding. Today, their algorithm is still considered a high bar for other algorithms to top. More recently, Elgendi et al. [6] developed an algorithm based on moving averages. It uses *a priori* knowledge about ECG signals, in this case about the width of QRS complex (or P wave) and the width of one beat. The widths are used to compute the width of moving average windows and are fixed throughout the signal.

P and T waves are usually detected with respect to R peaks (QRS complexes). Elgendi et al. [7] adapted their QRS detection algorithm to handle P and T waves, with promising results on a limited data set. *A priori* knowledge for P and T detection was based on estimates about the event duration before ECG processing. The average P wave width is estimated to be 110 ms ± 20 ms (the average was taken from measurements of healthy male adults with the heart rate of 60 beats per minute).

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Sun Y. et al. [8] developed an algorithm for detection of characteristic ECG waves based on morphological transformation. In this algorithm, multiscale morphological derivative (MMD) is used to distinguish important fiducial marks of characteristic waves: onsets, peaks, and offsets of P and T waves and Q, R, and S wave peaks.

From these researches, we can distinguish four processing steps in ECG characteristic wave detection algorithms, namely: noise and artifact reduction, transforms, fiducial marks selection of wave candidates and decision rule (similar to three steps reported in [5]). Based on those steps, in this work, we aim at adapting the described detection algorithms by combining certain steps for optimal waves' detection capabilities.

II. Methods

A. Data

Two databases are used for this research: MIT-BIH Arrhythmia Database [9] and QT database [10] from PhysioNet portal [11]. The databases are chosen based on the availability of both QRS and P and T wave annotations. P and T wave peak annotations for MIT-BIH Arrhythmia database were generously provided by Elgendi et al. [12].

MIT-BIH Arrhythmia database: The database contains 48 ECG recordings sampled at 360 Hz. The duration of each recording is 30 minutes. Recordings 102, 104, 107, and 217 were excluded from the analysis because of the paced beats presence. Recording 207 was also excluded due to great number of ventricular flutter waves. 60% of used records have annotated episodes of irregular heart rhythms, 70% of which include ventricular bigeminy, trigeminy or tachycardia. For all recordings, lead II is used to detect the characteristic waves.

QT database: The database contains 105 ECG records, which are sampled at (or resampled to) 250 Hz. The duration of each recording is 15 minutes. Only the last 5 minutes of the records are annotated. The records were taken from seven different databases. A section of ECG recordings is selected in order to avoid significant baseline wander or other artifacts. Between 30 and 100 representative beats were manually annotated by cardiologists in each record, who identified the beginning, peak, and end of P waves, the beginning and end of QRS-complexes, the peak and end of T waves, and (if present) the peak and end of U-waves [10].

We used only groups of contiguous annotated heartbeats with P and T wave annotations to determine the accuracy of detection, as proposed by Leutheuser et al. [13]. The recordings used are: *sel100*, *sel103*, *sel117*, *sel123*, *sel223*, *sel114*, *sel116*, *sel213*, *sel230*, *sel231 and sel233*.

Table 1. Number of records and annotated waves in the selected databases

Database	No. of records	R peaks	T waves	P waves
MIT BIH Arrhythmia	43	98 873	95 989	98 395
QT database	11	12044	452	452

The characteristics of used records from both databases is given in Table 1.

B. Algorithms

Detection of the characteristic waves can be categorized into two main groups: QRS complex detection (or R peak detection with additional Q and S detection) and P and T wave detection. These two groups are separated due to different frequency bands in which the main spectral components lie [14].

QRS detection

For QRS detection, ECG signal is filtered with Butterworth 3rd order bandpass filter with a frequency range of 5 – 15 Hz (Pan Tompkins) or 8 – 20 Hz (Elgendi). In addition, baseline and noise can be reduced using modified morphological filtering (MMF), as described in [15].

In the transformation step, operations that increase the rising slope of the signal are used. The Pan Tompkins' algorithm [5] uses squaring, differentiation, and integration transforms, Elgendi's algorithm [6] uses squaring and two moving averages, and Sun Yan's method uses MMD transforms [8]. The outputs of each transformation for a single ECG signal beat is shown in Fig. 1.

The next step in QRS detection is finding the fiducial marks that can be considered as candidates for R peaks. After that, a decision rule is applied. Pan Tompkins' algorithm finds fiducial marks as a rising slope or peak of the integrated waveform, after which the adaptive thresholding is applied [5]. Elgendi's algorithm searches for blocks where moving average with the window width of 35 samples (QRS) is greater than the moving average with window width of 220 samples (beat) [6]. Blocks with a width greater

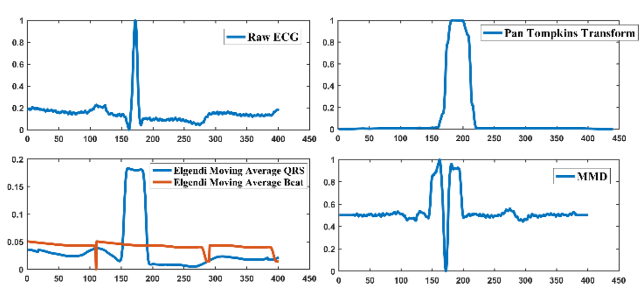

Fig. 1. Transformations on one beat in ECG signal (upper left: Raw ECG; upper right: Pan Tompkins Transform; down left: Elgendi Moving Averages (QRS and Beat); down right: MMD transform)

than the QRS length are marked as candidates, and the maximum value within that block is considered a detected R peak. Sun Yan's algorithm finds the local minimum values in the MMD signal and considers them as R peaks if they are greater in absolute amplitude than a set threshold, as determined from between-peak valleys in the histogram [8].

In this work, we implemented a fusion of algorithms by applying MMF noise and artefacts reductions step to Pan Tompkins' and Elgendi's algorithms and adaptive thresholding step of Pan Tompkins' algorithm to the selected fiducial marks. Also, MMD transformation step was implemented to test its behaviour within Elgendi's algorithm. Fig. 2 shows the decomposition of the described algorithms in four processing steps. The mathematical details of the specific steps for the inspected algorithms are given in the corresponding literature.

P and T wave detection

QRS detection is usually the first step of P and T wave detection, because a search for these waves is done with respect to R peaks. Elgendi's algorithm adapts moving average window widths to detect P and T waves.

We modified the Elgendi’s block search algorithm by applying the MMF noise and artefact reduction. Modification of Elgendi's algorithm with MMD step gave poor detection results and is therefore not presented here due to lack of space.

III. Results

We used sensitivity (*Se*) and positive predictive value (*+P*) for evaluating performance of detection algorithms. For determination of true positives (TP), sample deviation of 60 ms equivalent is used. Hence, if the detected wave is in the range of ± 60 ms from the annotated wave, the value is considered TP, and false positive (FP) otherwise. Similarly, if no detection of a wave was made in the range of ± 60 ms around annotation, the detection was considered false negative (FN). A 60 ms deviation is based on the normal QRS complex maximum expected width (120 ms). Some annotations are shown to be inconsistent (e.g. in records 108, 117, 208), often annotating S wave as R wave or annotating a point on R slope rather than the peak, and, as a result, performance with deviation required for precise HRV analysis (< 5 ms) is less accurate and not reported here.

In Tables 2–5, the results of the proposed algorithms are shown, with the best obtained combinations emphasized.

Table 2. MIT-BIH Arrhythmia Database R peak detection accuracy

Algorithm	TP	FP	FN	Se (%)	+P (%)
Pan Tompkins	98461	524	412	99.58	99.47
Elgendi	98515	376	358	99.64	99.62
MMF + Pan Tompkins	98313	605	560	99.43	99.39
MMF + Elgendi	**98650**	**277**	**223**	**99.77**	**99.72**
Elgendi + Adaptive Thresholding	97113	237	1760	98.22	99.76
MMD + Elgendi	97610	1218	1263	98.72	98.77
MMF + MMD + Elgendi	97939	874	934	99.06	99.12

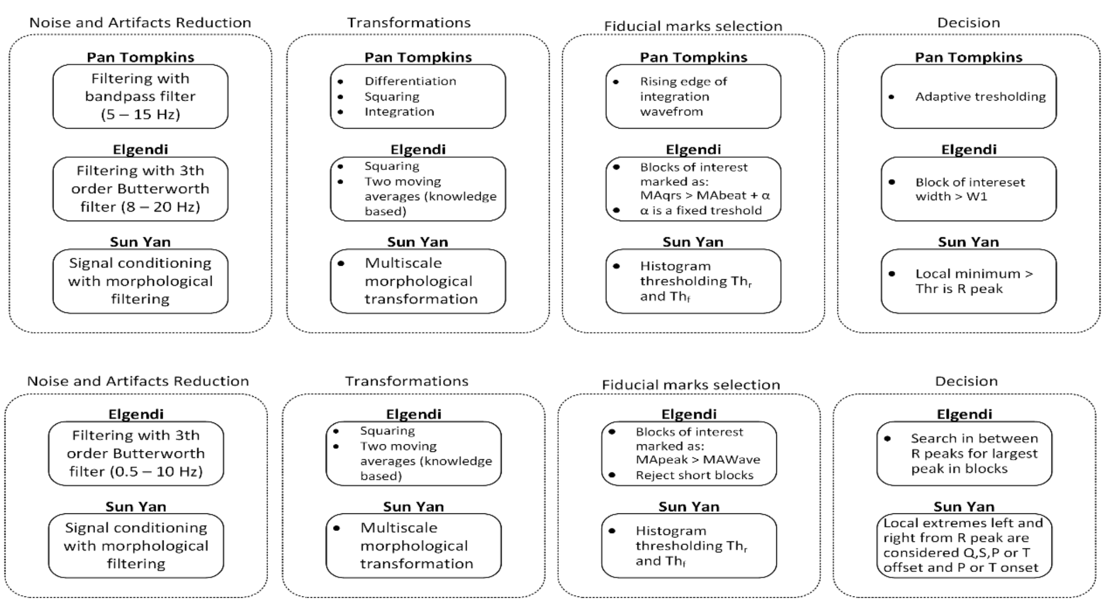

Fig. 2. Processing steps in detection algorithms of ECG characteristic wave

Table 3. QT Database R peak detection accuracy

Algorithm	TP	FP	FN	Se (%)	+P (%)
Pan Tompkins	11637	107	407	96.62	99.09
Elgendi	11962	84	82	99.32	99.30
MMF + Pan Tompkins	11931	110	113	99.06	99.09
MMF + Elgendi	11944	116	100	99.17	99.04
Elgendi + Adaptive Thresholding	11644	44	400	96.68	99.62
MMD + Elgendi	**12032**	**13**	**12**	**99.90**	**99.89**
MMF +MMD + Elgendi	12020	24	37	99.80	99.69

Table 4. MIT-BIH Arrhythmia Database P and T wave detection accuracy

Algorithm	TP	FP	FN	Se (%)	+P (%)
Elgendi P wave	**58404**	**39579**	**37585**	**60.84**	**59.61**
Elgendi T wave	**87365**	**6025**	**11030**	**88.79**	**93.55**
MMF + Elgendi P wave	52269	46451	43720	54.45	52.95
MMF + Elgendi T wave	87714	7489	10981	89.14	92.13

Table 5. QT Database P and T wave detection accuracy

Algorithm	TP	FP	FN	Se (%)	+P (%)
Elgendi P wave	**349**	**103**	**103**	**77.21**	**77.21**
Elgendi T wave	**328**	**124**	**124**	**72.57**	**72.57**
MMF + Elgendi P wave	75	73	377	16.59	50.68
MMF + Elgendi T wave	286	53	166	63.27	84.37

IV. Discussion and Conclusion

In this paper, we modified known algorithms for detection of characteristic waves in ECG. The modifications showed improvement of QRS detection methods when we use additional noise and artefact reduction step. The same step (MMF) gave less accurate results on P detection, probably due to small P amplitude mistaken for noise. The results for MMF + Elgendi for T wave detection, on the other hand, were similar to using only Elgendi's method.

The results for P and T wave detection overall gave less than satisfactory detection results. One of the main problems for accurate P and T waves detection is the small number of available annotated ECG records. As future work, we plan to expand our research and explore other known methods for ECG waves detection, such as [16,17], in order to establish the overall best detection combination.

Conflict of Interest

The authors declare that they have no conflict of interest.

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