Electrocardiogram Signal Analysing
Delineation and Localization of ECG Component

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Abstract: In this paper, we develop a new approach based on nonlinear filtering scheme (NLFS) on cardiac signal to evaluate a robust single-lead electrocardiogram (ECG) delineation system and waves localization method based on nonlinear filtering approach. This system is built in two phases, in the first phase, we proposed a mathematical model for detecting ECG features like QRS complex peak, P and T-waves onsets and ends from noise free of synthetic ECG signal. Later, we develop a theoretical model to obtain real approach for detecting these features from real noisy ECG signals. Our method has been evaluated on electrocardiogram signals of QT-MIT standard database, the QRS peak achieve sensitivity (Se) of 98.88 and a positive productivity (P+) of 98.43. For P-onset, P-end, T-end evaluations, this approach provides Sensitivity (Se) of 75.16, 71, and 90.7 respectively. Mean and standard deviation have been computed for differences between the automatic and manual annotations.

1 INTRODUCTION

The analysis of the ECG is widely used for diagnosing many cardiac diseases. Since most of the clinically useful information in the ECG is found in the intervals and amplitudes defined by its significant points (wave peaks and boundaries), the development of accurate, fast and robust methods for automatic and real time ECG delineation is one of basic research filed in biomedical engineering domain. As a matter of fact, QRS detection is necessary to determine the heart rate and as a reference for beat alignment. ECG wave delineation provides fundamental features (amplitudes and intervals) to be used in automatic analysis system. We can distinguish two main groups of algorithm in the topic of ECG features extraction. They are QRS detection algorithms and ECG waves delineation algorithms. QRS complex is the most notable wave in ECG signal which represents the duration of ventricular depolarization. Its high amplitude and steep slope make QRS detection easier than other waves. Thus it is generally used as a reference within the cardiac cycle. Many algorithms and approaches are proposed to solve QRS detection problem. A comprehensive review and classification these algorithms can be found in (Kohler et al., 2002). Concerning P and T-waves delineation, most algorithms start from predefined QRS complex and take a search window on the left and right of QRS complex to detect P and T-waves features onset, peak, and end respectively. Because of the low energy of P and T-waves, low signal to noise ratio, amplitude and morphological variability and possible overlapping of the P or T-wave with QRS complex, it is more difficult to delineate P and T-waves than QRS complex. Fig. 1 shows ECG signal interpretation with waves (P, T, U) and QRS complex position, different interval and waves delineation are indicated with the medical scale reference.

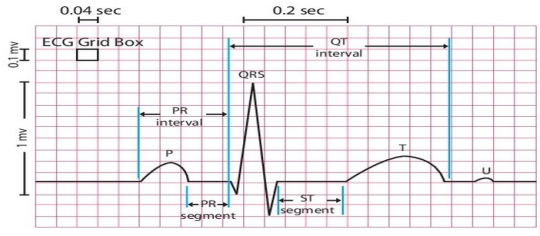

Figure 1: Normal ECG signal representation composed by P wave, QRS complex, T wave, U wave. Different intervals are shown with the medical scale reference.

In the literature, several approaches for P and T-waves delineation can be found. Approach of Lie et al (Lin et al., 2011) used Bayesian model, where as Mehta et al (Chouhan and Mehta, 2008) proposed a

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new method using Support Vector Machine approach, likewise Martinez et al (Martinez et al., 2004) introduced wavelet-based delineation algorithm. The validation of the most recent algorithms for QRS detection is based on standard database, but most of P and T-waves delineation approaches are not evaluated on standard databases. Thus leads to problem in comparing performance of these methods accurately. In this work, we present a new approach to detect QRS complex peak, P and T-waves onset/end points. The performance is validated on the QT MIT database (Laguna et al., 1997). This paper is organized as follows: in Section 2, the concept of 1D Nonlinear Filtering Scheme (1D NLFS) will be explained, then we will present the mathematical model for features extraction from free of noise synthetic ECG signal in Section 3. In Section 4, the real approach for features detection derived from previous mathematical model will be presented. Section 5 contains evaluation and testing for this approach and a comparison with other methods results. Conclusion and future works will be presented in Section 6.

2 1D NON LINEAR FILTERING SCHEME (NLFS)

In 1D NLFS presented in (Laligant and Truchetet, 2010), Laligant et al propose to achieve edge detection and noise reduction in one stage using nonlinear derivative approach. This approach solved the problem of delocalization that appears in derivative approaches as well. In this scheme, author proposed to localize the edge according to the sign of the transition slope. If the slope is positive, the edge will be localized after the transition; if the slope is negative, it will be localized before. For decomposing the signal, two detector filters are introduced $F_+(z)$ and $F_-(z)$ regularized without zero in the center and are given in Equation 1 :

$$F_+(z) = 1 - z^{-1} \; ; \; F_-(z) = -F(z-1) \qquad (1)$$

Author used a nonlinear operator T as a threshold for selecting the response. This scheme gives two signals given in equation 2: Y_+ which contains response for positive slope edge points, and Y_- which contains negative slope edge points.

$$Y_+ = T(F_+(z)S(z)) \; ; \; Y_- = -T(F_-(z)S(z)) \qquad (2)$$

We can simplify this approach as follow. Two derivative filtering processes of the signal are applied in two different directions. In each direction only the transitions with the same slope sign are retained as shown in the Fig. 2 and Fig. 3. The complexity of edge detection problem is reduced to the half by splitting the signal into two signals. This approach reduces the edge detection complexity into half by splitting the whole signal into two signals, each signal contains only one type of transitions; either with positive or negative slope.

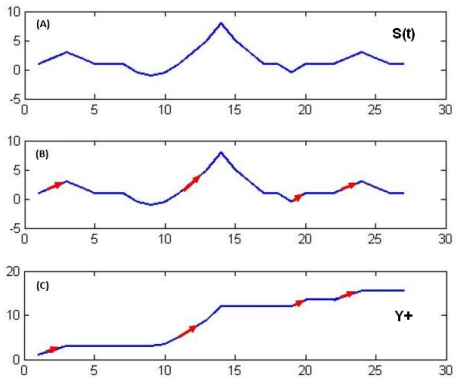

Figure 2: (A) Original signal S(t), (B) local positions of increasing changes of S(t), (C) Y+ signal corresponds to localization positions of increasing changes of S(t).

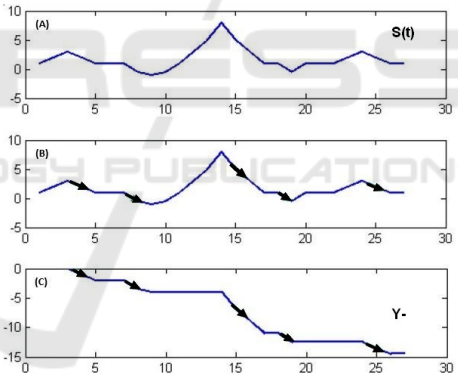

Figure 3: (A) Original signal S(t), (B) local positions of decreasing changes of S(t), (C) Y- signal corresponds to the positions of decreasing changes of S(t).

3 MATHEMATICAL MODEL

In this section, the mathematical model of our method that exploits Y_+, Y_- signals to detect QRS peak, P and T-waves Onset/End points will be presented. This model will be built upon free of noise synthetic ECG signal generated by a dynamical model method presented in (McSharry et al., 2003). Two main algorithms will be discussed in this model, two main algorithms, the first one for QRS peak detection, and the second for detecting onset/end of P and T-waves.

3.1 QRS Complex Detection

The detectig of QRS peak is the starting point for any ECG signal analysis process. So in this model, it will be detected as follows: Applying 1D NLFS on ECG signal to get Y_+ signal. Differentiating Y_+ signal to get to $difY+$ signal. Then, $difY+$ will be thresholded to set all its values that are under threshold to zero, whereas threshold value is 60% of the max value in $difY+$ signal. The $TdifY+$ signal is obtained, this signal contains a series of Gaussian peaks, each one of them corresponds to one QRS first rising half (QR segment). Linear search process within $TdifY+$ will be applied and the end of each peak gives the index of QRS peak after shifting it by two samples forward. Shifting forward is applied to compensate the part of peaks eliminated in thresholding step. Fig. 4 shows QRS peaks detections algorithm steps.

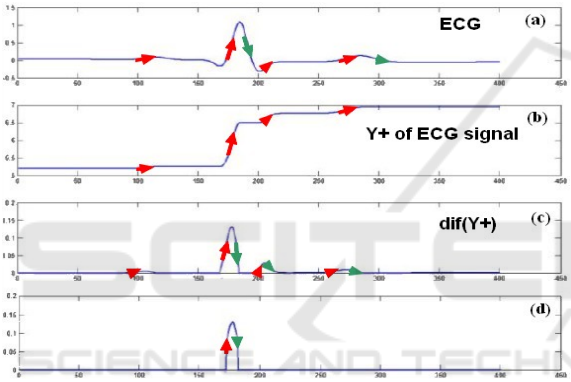

Figure 4: (a) Original ECG signal , (b) Y+: increasing changes of ECG signal, (c) dif (Y+): differentiation of Y+ signal, (d) TdifY+: threshold of dif(Y+) signal in order to obtain QRS complex localization.

3.2 P and T Waves Localization

QRS peak detection is used to determine boundaries of search windows that should contains P,T-waves. This search window falls on the right of QRS complex from T-wave and on the left from P-wave. After considering features of synthetic ECG model that represents free of noise normal ECG signal, boundaries of P and T-waves search window will be given by Equations (3) and (4). Once localized peaks R positions (Pos(R)) in QRS complex, we determine limitations (start and end positions) of search windows which should contain the airwaves P and T.

$$P_{on} = Pos(R) - 40ms;\ P_{end} = Pos(R) - \frac{RR}{2} \quad (3)$$

$$T_{on} = Pos(R) + 40ms;\ T_{end} = Pos(R) + \frac{RR}{2} \quad (4)$$

Where (P_{on}, T_{on}) and (P_{end}, T_{end}) represent respectively beginnings and ends of search windows that we want to detect onset/end points. RR represents the distance between two adjacent QRS peaks. The constant $40ms$ is determined via experiments on normal synthetic ECG signal. For onset point detection, The part of Y+ signal that falls between $w0$, $w1$ will be differentiated to give a feature signal that all its values are zeros except Gaussian peak starts at the onset of P or T-wave and end at the peak of P or T-wave. Linear search through this feature signal will be applied to find start of this Gaussian peak that corresponds to onset point. For end point detection, the part of Y-

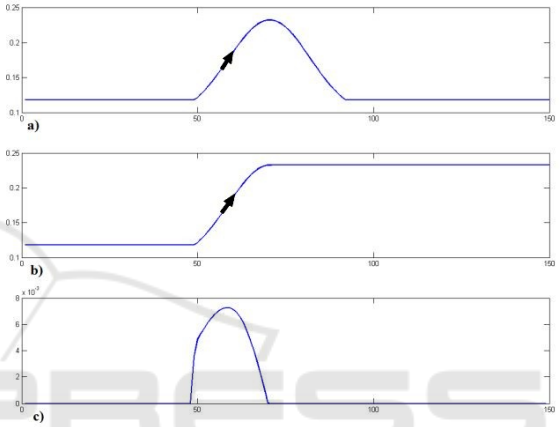

Figure 5: (a) P wave form, (b) Y+ signal corresponds to the positions of increasing changes of P wave, (c) dif(Y+) differentiation of Y+ signal.

signal that falls between $w0$, $w1$ will be differentiated to give a feature signal that all its values are zeros except Gaussian peak starts at the peak and ends at the end of P or T-wave. Linear search on this feature signal to detect the end of this peak that corresponds to end point will be applied. Fig. 5 and Fig. 6 show an example for of P-wave onset/end detection steps respectively. This mathematical model faces several challenges in real ECG signals like noise and variable morphologies of P and T- waves. These challenges make it inapplicable on real ECG signals. So, starting from this model we developed our approach for detecting QRS peak, P and T-waves onset/end points from real noisy ECG signals that will be presented in next section.

4 REAL ECG FEATURES EXTRACTION APPROACH

The backbone of this approach is the previous presented theoretical model. Real approach will show the

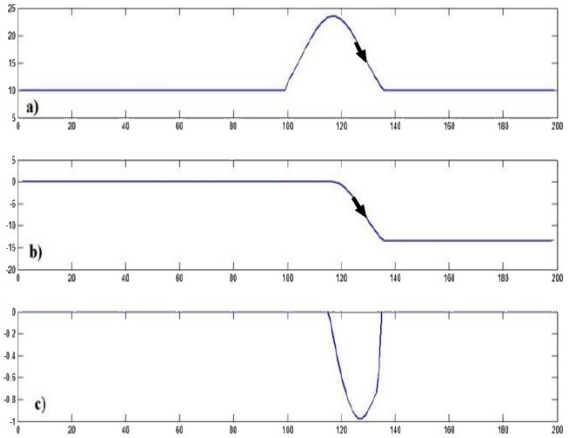

Figure 6: (a) P wave form, (b) Y- signal corresponds to the positions of decreasing changes of P wave, (c) dif(Y-) differentiation of Y- signal.

differences applied to overcome mathematical model challenges. Besides, we will discuss new challenges emerged in front of this approach, and what are the best ways to overcome them. This approach starts by QRS complex peak detection and proceeds for P and T-waves delineation.

4.1 Onset/End Points of P and T-waves Detection

Step 1: Preprocessing. The notable amplitude of QRS peak and the steep slope that it has are main two features that we are exploiting in our derivative approach to build QRS peak detection algorithm. In real ECG signal, sharp noise transitions could be existed in the signal. These sharp noise singularities could be detected as QRS complex because they have same features of high amplitude and steep slope. So, moving average filter to eliminate such singularities has been applied on ECG signal. **Step 2: 1D NLFS.** After filtering, 1D NLFS approach has been applied on the filtered ECG signal to get, Y+ signal. **Step 3: Obtaining Feature Signal.** Applying differentiation process on the Y+ signal to get difY+ signal. The main purpose of this process is converting the rising transition in this signal into Gaussian peaks. Then, thresholding difY+ to get TdifY+ signal which set all its values to zero except which are higher than Thresh value determined in equation (5).

$$Thresh = 0,6 * max(difY_{+}) \quad (5)$$

Step 4: Linear Search. Linear search process will be applied on $TdifY+$ signal, and register the index of the end of each peak. **Step 5: QRS Peak Detection.** After determining the end of each peak $w0$, a narrow search window around it on the original ECG signal ECG ($w0$-5, $w0$+5) will be defined. Within this narrow window, the local maximum value will be considered as QRS peak point. **Step 6: Iteration.** Repeat Step 4 and 5 either up to detecting all required R peaks in the signal or up to reach the end of the signal. **Step 7: Defining RR Line.** Subtract the index of each R peaks from previous R peak index value to find RR line which represents the heart rate.

4.2 P and T-wave Delineation in Real ECG Signal

To give clear indication about how much this approach is robust to noise, we will delineate P and T-waves in *QTMIT* database that contains certain amount of noise without using any denoising procedure in this part of our approach. The first step in detecting onset/end points is determining boundaries of search window that contains P and T-waves. These boundaries will be defined exactly in the same way used in the mathematical model and given in equations (3), (4). Obtaining feature signal by normal differentiation step on Y+, Y- as we did in the mathematical model is not efficient. The main two reasons are the noise that comes from different sources to ECG signal and the changes in amplitude of real ECG signal between main cardiac waves like P, QRS and T waves that comes basically from muscles electrical activity.

$$S(i) = Y(i+8) - Y(i) \quad (6)$$

The proposed solution for this problem is applying differentiation process with a wide step about 32 ms for parts of Y+, Y- that fall in region of interest i.e. between $w0$, $w1$. The sampling rate in *QTMIT* database ECG signals is 250 Hz (i.e: 32 ms) equals 8 samples (sp). This differentiation step will reduce the effect of noise and still gives a clear indication for onset/end position within Y+, Y-. Equation (6) shows the feature signal obtained for detecting onset/end points: As in the mathematical model, Y+ signal is used for onset points detection by considering the index of maximum value in S(i) feature signal as index for onset point. Y- Signal is used for end points detection by considering the index of minimum value in S(i) feature signal as index of end point after shifting it forward with 8 samples.

4.3 Limits of NLFS Approach Applied on Real ECG Signal

Like other methods and approaches in this field of research, this approach has its own limits like:

1) Static thresholding used in *QRS* peak detection algorithm: fixed threshold is used for this task, and this fixed thresholding may lead to false positive detection in some rare cases of ECG signal such as record 117 in MIH-BIT Arrhythmia database (Moody and Mark, 2001) where height of T-wave amplitude is more or less the same of *QRS* complex amplitude.
2) Static boundaries determination for search windows to detect onset/end points of P or T-wave: In some special cases of ECG signal P or T-wave is overlapped with QRS complex. This overlapping makes onset/end points fall out of search window.
3) Dependency of onset/end detection: P and T-waves delineation is started from QRS peak defined in previous step. So, if there is error in R peak detection this will lead to error in P and T-waves delineation.
4) There are unusual morphologies for P and T-waves could be existed in real ECG signals like inverted or bi-phasic waves, presented approach unable to deal with them.

5 EVALUATION AND TESTING

Because there is no golden rule to determine the peak, onset and end of the ECG waves, the validation of such algorithms must be done using manually annotated databases like *QTMIT* database [5]. This database was developed for wave limits validation purposes and it provides cardiologist annotations for at least 30 beats per recording, with marks including *QRS* complexes, P and T waves peaks, onsets and ends. The *QTDB* also includes, for 11 out of its 105 records, an additional annotation performed by a second cardiologist. Twelve records from this database are selected to calculate the mean error (ME), Standard Deviation (SD) for difference between our approach detection and manual annotations existed. Then we calculate the Sensitivity (Se) and the Positive Predictivity (P+) values. Se=TP/(TP+FN), and P+=TP/(TP+FP). Where TP represents True positive, FP represents False Positive, FN represents False Negative parameters. For deciding to any one of these choices our approach detection results belong, we will consider standard deviation accepted error by cardiologist in any ECG automatic analysis system presented in (Zywietz and Celikag, 1991).

Table. 1 shows standard deviation σ in (ms) of maximum accepted error for these points detection.
Table. 2 shows the result of applying our approach on the subset of QTMIT database that contains about 300 annotated beats. We can note there is no result for T-onset point, because it is not annotated manually in QTMIT database. The visual observation shows that the performance of our approach for T-onset point should be close to T-end point performance.

Table 1: Accepted tolerances for standard deviation accepted error σ (ms) by cardiologist in any ECG automatic analysis.

Localization	P_on	P_{end}	QRS_on	QRS_end	T_end
$\sigma(ms)$	10.2	12.7	6.5	11.6	30.6

Table 2: Performance on subset of *QTMIT* database.

	ME (ms)	SD (ms)	Se	P+
P_{onset}	1.48	11.55	75.16	75.16
P_{end}	-1.747	13.57	71	71
R_{peak}	-3.251	2.487	98.43	98.88
T_{end}	-7.93	12.396	90.7	90.7

For comparing results of this current work with the best algorithms and approaches in this field of research, this approach gives good results in general as a first version of this approach. It gives less competitive results for P-wave onset/end points, and gives good performance for T-end. For QRS peak detection gives good and competitive results. Despite it gives lower values numerically, it is still promising approach for following reasons: 1) It represents the first initiative to exploit 1D NLFS approach in signal decomposition. 2) It is single-lead based, fast and robust to noise approach which makes it convenient for real time ECG analysis systems. 3) There are several enhancements could be done on this work which can lead to enhance its performance and decrease its limitations.

Table. 3 represents a comparison among this approach and best existing approaches in this field like wavelet- approach presented in (Martinez et al., 2004), and Low Pass Differentiation approach presented in (Laguna et al., 1994), and Bayesian detection-estimation algorithm presented in (Lin et al., 2011). We can note that our approach gives lower standard deviation error and lower Sensitivity Positive. In Table. 3 we can note that our approach gives lower standard deviation error and lower Sensitivity, Positive Predictivity in the same time. The main reason may be behind this paradox that other approaches used wider accepted error than we considered in our approach for calculating Se, P+. Table. 3 shows QRS complex localization and delimitation by applying NFLS approach on electrocardiogram signals from QTMIT database, these results are obtained quickly and with high precision.

6 CONCLUSION

In this work, a new single-lead based fast and robust to noise approach for ECG signal features detection is presented. This algorithm could be exploited as a part

Table 3: Results comparison of the proposed method with other methods.

Method	Parameters	P_{on}	P_{end}	QRS	T_{end}
Proposed method	Se (%)	75.16	71	98.88	90.7
	P+(%)	75.16	71	98.88	90.7
	m± s (*ms*)	1.48 ± 11.5	-1.7± 13.5	-3.2± 2.48	-7.9 ± 12.3
WT[4]	Se (%)	98.87	98.75	99.92	99.77
	P+(%)	91.03	91.03	99.88	97.79
	m± s (*ms*)	2.0 ± 14.8	1.9± 12.8	NA	-1.6 ± 18.1
LPD [10]	Se (%)	97.70	97.70	NA	99.90
	P+(%)	91.17	91.17		97.71
	m± s (*ms*)	14 ± 13.3	-0.1± 12.3		13.5 ± 27.0
Bayes[2]	Se (%)	99.6	99.6	NA	100
	P+(%)	NA	NA		NA
	m± s (*ms*)	1.7 ± 10.8	2.5± 11.2		2.7 ± 13.5

of automatic analysis system for cardiac diagnosis. We exploited for the first time the concept of signal decomposition into two sub signals, each one of them contains half of the information. This decomposition reduces problem complexity especially for onset/end points detection algorithm. We started by proposing theoretical model to show how we can extract important information from free of noise synthetic ECG, then this model is developed to present real approach that can deal with real noisy ECG signals. This approach is a comprehensive algorithm existed nowadays, because most of current algorithms either for QRS complex detection or for P and T-waves delineation depending on predefined QRS complex. Testing has been done on twelve records from QTMIT standard database to calculate mean error, standard deviation, Se, P+. This approach gives good results for QRS peak, T-end points and less competitive than other approaches for P-wave onset/end points. The future works could be useful for improving performance of this approach could be summarized as follows: 1) Improving static thresholding procedure used within QRS complex peak detection, to be dynamic and robust even for special rare clinical cases could be faced in real ECG signals. 2) Using dynamic and adaptive differentiation steps instead of static one for obtaining feature signal from Y+, Y- can increase the performance accuracy. 3) Adding denoising stage beforeonset/end points detection will lead to improve performance ofthis approach. 4) Generalizing this approach to be applicable to detect peak, onset and end points from other type of signals.

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