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A Simple and Robust Algorithm for the Detection of QRS Complexes

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Abstract—The objective of this paper is to develop an easy, efficient and robust algorithm for the analysis of electrocardiogram signals. The technique used in this algorithm is based on the use of Moving Average Filters and Adaptive Thresholding for QRS complex detection. Several established ECG databases published on PhysioNet with sampling frequency ranging from 128Hz-
1KHz, were used for analyzing the technique. The accuracy of the algorithm is determined on the basis of two statistical parameters: sensitivity (SE) and Positive Predictivity (+P).

Index Terms—Electrocardiogram, Moving Average Filter, adaptive thresholding, sensitivity, positive predictivity.

I. INTRODUCTION

The electrocardiogram (ECG) signal represents the electrical activity of the heart over a period of time. It picks up electrical impulses generated by the polarization and depolarization of cardiac tissue and translates it into a waveform. since the QRS complex reflects the ventricular contraction, the time of its occurence as well as its shape provides much information about the present state of the heart. Also, because the QRS complex has a characteristic shape, it serves as the basis for automated determination of the heart rate which is the first step in the diagnosis of the cardiac cycle. Thus, QRS detection provides the fundamentals for almost all automated ECG analysis algorithms.

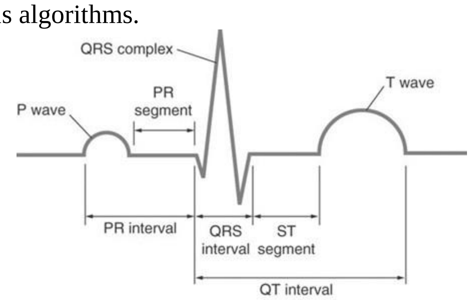


Fig. 1. Typical ECG waveform

Software QRS detection has been a research topic for the past 30 years. Because of the physiological variability of the QRS wave, and also to the presence of noise and artifacts in the ECG signal, so far no QRS detection technique has been reported to provide 100 % accuracy. A QRS detection algorithm has, in common, the stages of pre-processing, which includes linear and non-linear filtering of the signal to remove noise and artifacts as well as enhance the QRS complex to other waves. It is then followed by feature extraction, which results in temporal location of the QRS complex on the basis of slope determination, amplitude and width of QRS complex, duration of wave etc. finally, decision-making, which is rather heuristic and dependent on the pre-processing results.

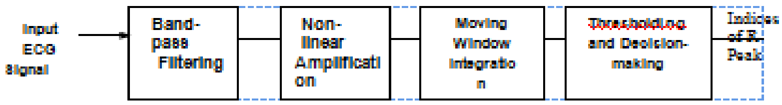
There are a number of algorithms some of which are used for the detection of all the ECG wave segments, namely P, QRS, and T, while the others deal only with the detection of QRS complexes. The earlier approaches towards ECG waves detection employed methods like power spectral analysis of ECG waveforms, as well as of isolated QRS complexes and episodes of noise and artifacts [7]. An algorithm based on digital analysis of slope, width and amplitude of ECG signal was developed by Pan and Tompkin (1985) [3] . This algorithm used digital band-pass filter for pre-processing of the signal, followed by differentiation for determining the slope of the signal. The algorithm was very reliable and therefore, a popular method for QRS detection but, it had a limitation that its filters were designed only for ECG signals sampled at 200Hz. Laguna *et al* (1992) [8] developed a method to determine automatically the characteristic points (onset and offset) of P, QRS, and T waves in multilead ECG signals from CSE DS-3 database. This method makes use of a differentiated, low- pass filtered ECG signal. An approach based on mathematical morphology operator for QRS detection was suggested by Trahanias (1993) [13]. This Morphological operator works as a peak-valley extractor. Li *et al* (1995) [9] used quadratic spline wavelet technique on the MIT/BIH database. Vijaya *et al* (1997) [10] developed a method which is based on an artificial neural network (ANN). Maheshwari *et al* (1998) [11] developed an analytical technique using the spatial velocity approach that detects the QRS complexes and thereafter, ex- tracts P and T waves. An Adaptive Hermite Model Estimation System (AHMES) is presented by Laguna *et al* (1996) [12] for online beat-to-beat estimation of the features of the ECG signal.

All the methods mentioned above claim appropriate and satisfactory results for ECG wave detection but methods based on ANN and AHMES require exhaustive training, settings and estimation of model parameters. Thus, they are computationally complex and time consuming. To reduce the computational cost as well as time, a simple and easy to implement algorithm was devoloped by H.C. Chen and S.W. Chen (2003) [1]. This algorithm used moving average filters for real-time QRS detection. In this work, an algorithm making use of IIR filter in the pre-processing stage and moving average filter for feature extraction of the QRS complex is designed. The above algorithm has been tested for its robustness and accuracy using different standard databases form PhysioNet.

This paper is organized in the following sequence: section II describes the methodology used for detection of QRS complex. The results are presented in section III, followed by conclusion in section IV.

II. METHODOLOGY

Fig. 2 displays a schematic block diagram of the proposed QRS detection algorithm. The input ECG signal first under- goes pre-processing, for the removal of noise and artifacts from the signal, followed by a non-linear amplification, which includes squaring and moving window integration resulting in an envelope-like feature waveform. Finally, an adaptive threshold is applied to the feature waveform to perform the task of decision-making for completing a QRS complex detection.



A. Detection of QRS complexes

1) Band-pass Filter: Morphologies of normal and abnormal QRS complexes differ widely. The ECG signal is often corrupted with low frequency noises like baseline wander, 60Hz powerline interference, muscle noise, P- and T-wave interference. Typical frequency components of a QRS complex range from about 10 Hz to 25 Hz [4]. Therefore, we use a third-order Butterworth filter with a passband of 8-20 Hz [5]. Butterworth filter offers a good transition band characteristics at low coefficient orders, which makes it efficient to implement.

2) Squaring: The signal is squared point by point. This is known as non-linear amplification. It makes all the data points positive thereby, emphasizing on the higher frequencies(i.e., the ECG frequencies). The squaring operation is performed as follows;

$$y[n]=(x[n])^2 \qquad (1)$$

3) Moving Window Integration: The purpose of moving window integration or summation is to smoothen the squared ECG signal thereby, producing an envelope like feature wave- forms. It is calculated as;

$$MA_{QRS}[n] = \frac{1}{W_1}(y[n-(W_1-2)/2] + \cdots + y[n] + \cdots + y[n+(W_1-2)/2]) \qquad (2)$$

Where, W_1 is the window size and y[n] is the squared ECG signal. Moreover, the width of the moving summation window is very important. Generally, the width of the window should be approximately same as the widest possible QRS complex. In this algorithm the size of the moving window is determined by a prior knowledge base, i.e., the QRS duration in a normal healthy subject varies from 29 to 43 samples, for a sampling frequency of 360Hz [5]. Therefore, we have taken the value of W1 as 35 samples.

4) Thresholding and Decision-making: The moving window integration yields an envelope like ECG waveform which consists of QRS complexes. An adaptive threshold is then applied to this signal for decision-making. The threshold is updated as;

$$\text{Threshold}=\alpha\times\gamma\times\text{PEAK}+(1-\alpha)\times\text{Threshold} \quad (3)$$

where PEAK is the newly detected local maxima in the feature waveform, α is referred to as the "forgetting factor", and is restricted to the positive numbers, that is, $0 \leq \alpha \leq 1$. γ is called weighing factor and it can be between 0.15 to 0.2 [1]. Blocks of interest are generated where the value of feature signal exceeds the threshold values. The maximum or peak value in these blocks of interest is taken R- wave. On the left side of this newly detected R- peak, the local minima is called as Q- wave. similarly, on the right side of the R- peak the local minima is taken as S- wave. The value of threshold is updated each time a QRS complex is detected. Fig. (3) shows the QRS algorithm detection steps as applied on ECG signal 100.dat from MIT/BIH database. (a) shows the original ECG signal, (b) shows the signal after band-pass filtering, (c) shows the signal after squaring, (d) shows the result of moving window integration, (e) shows the generated blocks of interest and, (f) shows the ECG signal with QRS fiducial points.

III. RESULTS

A. QRS detection algorithm

The QRS detection algorithm used in this paper has been tested on a small subset of five standard ECG databases taken from PhysioNet [16]. They are; MIT/BIH arrhythmia database, Meta dataset QT database, ST change database, Superaventricular arrhythmia dataset and Intracardiac atrial fibrillation database. All these datasets have their sampling frequencies between 128Hz − 1Kz. The algorithm has been tested on the basis of two statistical measures, i.e., sensitivity(SE), and

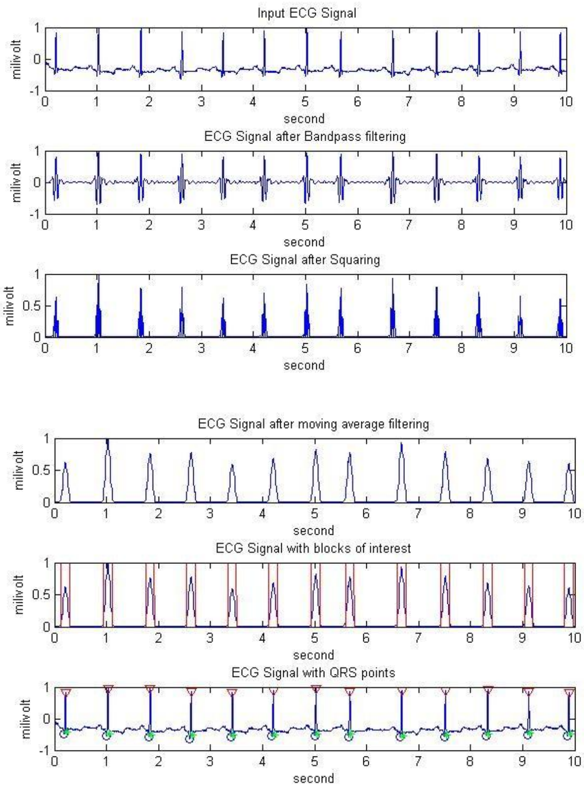


Fig. 3. QRS detection algorithm processing steps for MIT100 signal positive predictivity(+P).

$$SE = \frac{TP}{TP + FN}; \quad (4)$$

and;
$$+P = \frac{TP}{TP + FP}$$

where, TP is the number of true positives (QRS complexes detected correctly), FP is the number of false positives (non-QRS complexes detected as QRS complexes), and FN is the number of false negatives (QRS complexes have not been detected as QRS complexes).

The reason for testing this algorithm for other databases is to examine the robustness of the algorithm. The algorithm has not been re-tuned for any parameters other than the MIT-BIH Arrhythmia Database. The parameters used in this algorithm i.e., passband frequency, width of moving window are set for ECG signal with sampling frequency 360Hz.

IV. CONCLUSION

An efficient and robust algorithm for the detection of QRS complex is presented in this work. The QRS detector was designed for MIT-BIH Arrhythmia Database only, but it has

TABLE I
QRS Detection Performance On Standard Databasess

Database	Sampling Frequency	SE(%)	+P(%)
MITDB	360Hz	99.2	98.7
QTDB	250Hz	98.7	99.1
STDB	360Hz	97.4	96.1
SVDB	128Hz	90.8	85.1
IAFDB	1KHz	98.1	91.4

also been tested on other standard databases also without any additional tuning of parameters. We have obtained high sensitivity even when the algorithm has been applied on other signals also. Since the QRS detector has not been re- tuned over any database, its robustness is proved. Therefore, the algorithm can detect R- peaks over different databases, sampling frequencies, types of arrhythmia and type of noise.

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