A Novel Algorithm for ECG Signal Processing

[1]Padma Batra, [2]Rajiv Kapoor
[1]Dept. of ECE, Krishna Institute of Engineering and Technology, Ghaziabad, UP, India
[2]Dept. of ECE, Delhi Technological University, Delhi, India

Abstract
Research in computerized electrocardiography is heading towards stagnation but very little efforts have been made for popularizing it and ensuring its availability to the masses. Although the quantitative ECG is superior to its conventional counterpart but the former is yet to be accepted in clinical practice in India. An attempt has been made o develop quantitative ECG acquisition and classification system. Many approaches has been proposed to detect QRS complex in ECG signal. We have developed a real time algorithm for detection of QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital analyses of slope, amplitude and width. This algorithm automatically threshold parameters periodically, using mat lab and can be implemented where hardware cannot be carried for example, in remote areas, at military sites, even for personal homecare system.

Keywords
QRS Detection, Disease Classification, Real Time Based Algorithm

I. Introduction

The QRS complex is generally chosen for the detection of Cardiac arrhythmias, such as an irregular heart rate. The detection of QRS complex, specifically, the detection of the peak of the QRS complex, or R wave, in an ECG signal is a difficult problem since it has a time-varying morphology and is subject to physiological variations due to the patient and to corruption due to noise.

The rapid development of powerful microcomputers promoted the widespread application of software QRS detection algorithms [1] in cardio logical devices. Beginning about 30 years ago, software QRS detection has replaced more and more hardware QRS detectors.

Already in the early years of automated QRS detection, an algorithmicstructure was developed that is now shared by many algorithms. As shown in fig. 2 it is divided into a preprocessing or feature extraction stage including linear and nonlinear filtering and a decision stage including peak detection and decision logic. Often an extra processing

block is used for the exact determination of the temporal location of the assumed QRScandidate. In this article the different algorithms are discriminated with respect to their preprocessing stages, because most of the decision stages are rather heuristic and dependent on the preprocessing results [2].

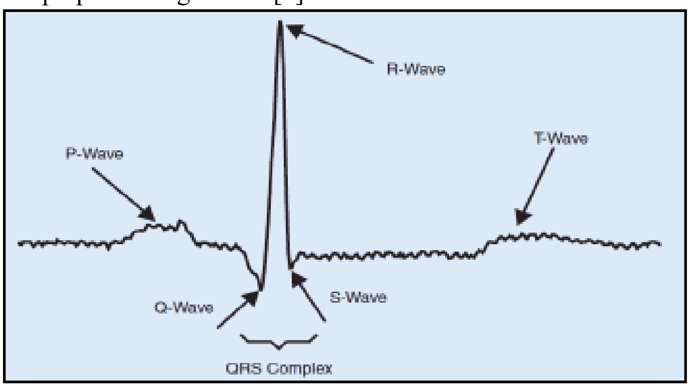


Fig. 1: QRS Complex in ECG Signal

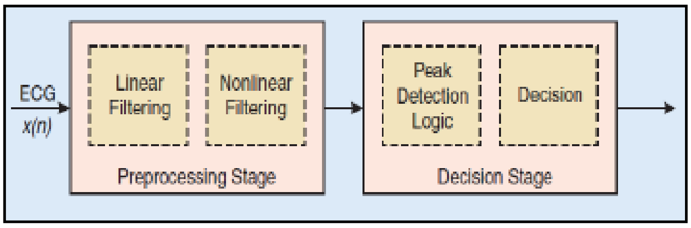


Fig. 2: QRS Detector

II. Methods for QRS Detection

A. Approaches Based on Signal Derivatives and Digital Filters

Typical frequency components of a QRS complex range from about 10 Hz to about 25 Hz. Therefore, almost all QRS detection algorithms use a filter stage prior to the actual detection in order to attenuate other signal components and artifacts, such as P-wave, T-wave, baseline drift, and in coupling noise [4]. Whereas the attenuation of the P- and T-wave as well as baseline drift requires high-pass filtering, the suppression of in coupling noise is usually accomplished by a low-pass filter [22].

The combination of low and high passmeans effectively the application of a band pass filter, in this case with cut-off frequencies at about 10 Hz and 25 Hz.

B. Neural Network Approaches

Artificial neural networks have been widely applied in nonlinear signal processing, classification, and optimization. In many applications their performance was shown to be superior to classical linear approaches.

In ECG signal processing, mostly the multilayer perceptron (MLP), radial basisfunction (RBF) networks, and learning vector quantization (LVQ) networks areused [15].

C. Hidden Markov Models

HMMs model the observed data sequence by a probability function that varies according to the state of an underlying (hidden) Markov chain. By means of the Markov chain the global structural characteristics of the process are preserved while the parameters of the probability density function account for the varying statistical properties of the observed data. The objective of the algorithm is to infer the underlying state sequence from the observed signal. In the case of ECG signals, possible states are P-wave, QRS, and T-wave. The advantage of this detection method is that not only the QRS complex is determined but also P- and T-waves. Problems of the method include a necessary manual segmentation for trainingprior to the analysis of a record, its patient dependence, and the considerable computational complexity even when the computationally efficient Viterby algorithm [20] is applied.

D. Matched Filters

Besides the neural-network-based matched filtering approach, thereare linear matched filtering approaches. After some analog preprocessing steps such as an automatic gain control, the ECG signal is digitized and further processed by a comb filter (low

 ISSN : 0976-8491 (Online) | ISSN : 2229-4333 (Print)

pass) with a notch at 50 Hz and a band pass filter with cut-off frequencies at 15 Hz and 40 Hz. This digital filter stage is followed by a matched filter for further improvement of the Signal-to-Noise Ratio (SNR).

E. Wavelet

An alternative approach based on mathematical tools, known as wavelet transforms, has emerged over the past decades for its possible applications to ECG signal processing Wavelet transforms produce a time-frequency decomposition of the signals, which results in individual signal frequency components [5]. This decomposition is based on a basic waveform, called the mother wavelet, which is scaled (dilated or compressed) and shifted to produce different members of the decomposed set of signals. Each member represents some features of the original signals in terms of time and frequency, depending on the scaling and shifting factors [15]. In ECG analysis this results in the opportunity to separate individual Components according to their frequency and time information, into different scales and analyze each scale individually. The wavelet transform at small scales reflects the high frequency components of the signal and at large scales reflects the low frequency components of the signal [20].

III. Proposed Method

The method which we propose recognizes QRS complexesbased on analyses of the slope, amplitude, and width.Figure 3.8 shows the various filters involved in the analysis of the ECG signal.In order to attenuate noise, the signal is passed through a band pass filter composedof cascaded high-pass and low-pass integer filters [6]. Subsequent processes are differentiation, and time averaging of the signal.

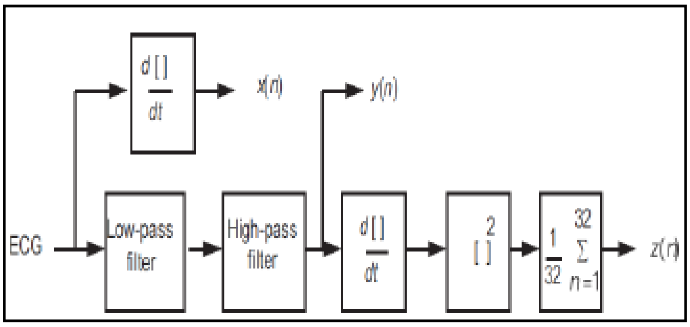


Fig. 3: Block Diagram for QRS Detection Technique

We designed a band pass filter from a special class of digital filters that require only integer coefficients. This permits the microprocessor to do the signal processing using only integer arithmetic, thereby permitting real-time processing speeds that would be difficult to achieve with floating-point processing. Since it was not possible to directly design the desired band pass filter with this special approach, the design actually consists of cascaded low-pass and high-pass filter sections. This filter isolates the predominant QRS energy centered at 10 Hz, attenuates the low frequencies characteristic of P and T waves and baseline drift, and also attenuates the higher frequencies associated with electromyography noise and power line interference [21]. The next processing step is differentiation, a standard technique for finding the high slopes that normally distinguish the QRS complexes from other ECG waves [2].

To this point in the algorithm, all the processes are accomplished by linear digital filters [10]. Next is a nonlinear transformation that consists of point-by-point squaring of the signal samples.

This transformation serves to make all the data positive prior to subsequent integration, and also accentuates the higher frequencies in the signal obtained from the differentiation process. These higher frequencies are normally characteristic of the QRS complex. The squared waveform passes through a moving window integrator. This integrator sums the area under the squared waveform over a 150-ms interval, advances one sample interval, and integrates the new 150-ms window. We chose the window's width to be long enough to include the time duration of extended abnormal QRS complexes, but short enough so that it does not overlap both a QRS complex and a T wave. Adaptive amplitude thresholds applied to the band pass-filtered waveform and to the moving integration waveform are based on continuously updated estimates of the peak signal level and the peak noise. After preliminary detection by the adaptive thresholds, decision processes make the final determination as to whether or not a detected event was a QRS complex. A measurement algorithm calculates the QRS duration as each QRS complex is detected. Thus, two waveform features are available for subsequent arrhythmia analysis—RR interval and QRS duration.

Over the past few years, there has been an increased trend toward processing of the Electrocardiogram (ECG) using microcomputers. A survey of literature in this research area indicates that systems based on microcomputers can perform needed medical services in an extremely efficient manner. In fact, many systems have already been designed and implemented to perform signal processing tasks such as 12-lead off-line ECG analysis, Holter tape analysis, and real-time patient monitoring. All these applications require an accurate detection of the QRS complex of the ECG. For example, arrhythmia monitors for ambulatory patients analyze the ECG in real time (Pan and Tompkins, 1985), and when an arrhythmia occurs, the monitor stores a time segment of the abnormal ECG. This kind of monitor requires an accurate QRS recognition capability [10]. Thus, QRS detection is an important part of many ECG signal processing systems. This chapter discusses a few of the many techniques that have been developed to detect the QRS complex of the ECG. It begins with a discussion of the power spectrum of the ECG and goes on to review a variety of QRS detection algorithms.

A. Band Pass Filter

The band pass filter for the QRS detection algorithm reduces noise in the ECG signal by matching the spectrum of the average QRS complex. Thus, it attenuates noise due to muscle noise, 60-Hz interference, baseline wander, and T-wave interference [21]. The pass band that maximizes the QRS energy is approximately in the 5–15 Hz range. The filter implemented in this algorithm is a recursive integer filter in which poles are located to cancel the zeros on the unit circle of the z plane. A low-pass and a high-pass filter are cascaded to form the band pass filter.

B. Derivative

After the signal has been filtered, it is then differentiated to provide informationabout the slope of the QRS complex.

Note that the amplitude response approximates that of a true derivative up to about 20 Hz.This is the important frequency range since all higher frequencies are significantly attenuated by the band pass filter is the resultant signal after passing through the cascade of filtersincluding the differentiator. Note that P and T waves are further attenuated while the peak-to-peak signal corresponding to the QRS complex is further enhanced.

C. Squaring Function

The previous processes and the moving-window integration, which is explained in the next section, are linear processing parts of the QRS detector. The squaring function that the signal now passes through is a nonlinear operation. The equation that implements this operation makes all data points in the processed signal positive, and it amplifies the output of the derivative process nonlinearly. It emphasizes the higher frequencies in the signal, which are mainly due to the QRS complex [6]. A fact to note in this operation is that the output of this stage should be hard limited to a certain maximum level corresponding to the number of bits used to represent the data type of the signal.

D. Moving Window Integral

The slope of the R wave alone is not a guaranteed way to detect a QRS event.Many abnormal QRS complexes that have large amplitudes and long durations (notvery steep slopes) might not be detected using information about slope of the Rwave only. Thus, we need to extract more information from the signal to detect event [23].Moving window integration extracts features in addition to the slope of the Rwave.

The width of the window should be approximately large; the integration waveform will merge the QRS and T complexes together. On the other hand, if the size of the window is too small, a QRS complex could produce several peaks at the output of the stage [6]. The width of the window should be chosen experimentally. For a sample rate of 200 sample per second, the window chosen for this algorithm was 30 samples wide (which correspond to 150 ms).

E. Thresholding

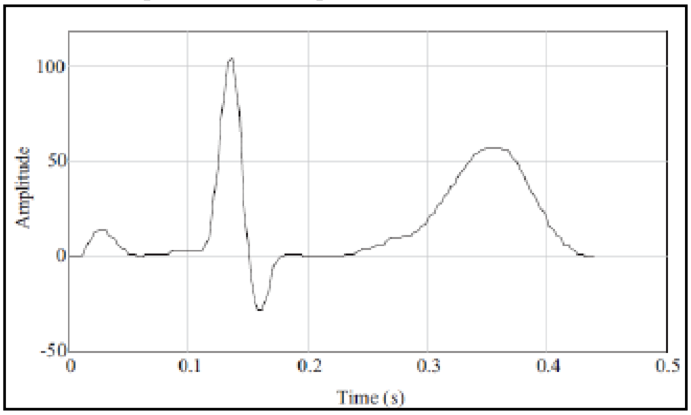
The set of thresholds used for this stage of the QRSdetection algorithm were set such that signal peaks (i.e., valid QRS complexes)were detected [13]. Signal peaks are defined as those of the QRS complex, while noisepeaks are those of the T waves, muscle noise, etc. After the ECG signal has passed through the band pass filter stages, its signal-to-noise ratio increases. This permitsthe use of thresholds that are just above the noise peak levels.

IV. Resultsand Discussion

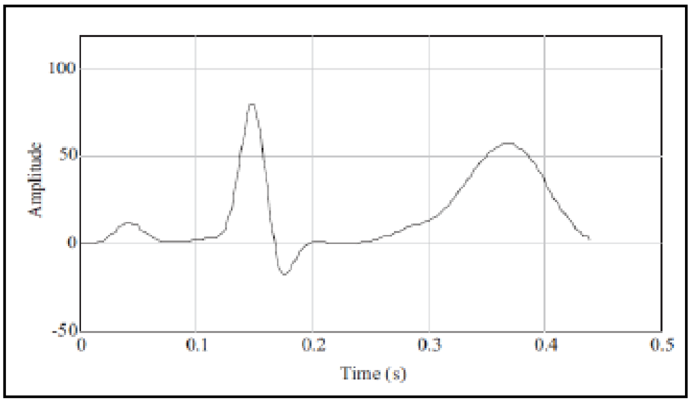
We have developed a real time algorithm for detection of QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital analyses of slope, amplitude and width. This algorithm automatically computes the threshold parameters periodically, using matlab.It recognizes QRS complexesbased on analyses of the slope, amplitude, and width. Band pass filter isolates the predominant QRS energy centered at 10 Hz, attenuates the low frequencies characteristic of P and T waves and baseline drift, and also attenuates the higher frequencies associated with electromyography noise and power line interference. The next processing step is differentiation, a standard technique for finding the high slopes that normally distinguish the QRS complexes from other ECG waves.Next is a nonlinear transformation that consists of point-by-point squaring of the signal samples to make the entire data positive prior to subsequent integration, and also attenuates the higher frequencies in the signal obtained from the differentiation process. The squared waveform passes through a moving window integrator. This integrator sums the area under the squared waveform over a 150-ms interval, advances one sample interval, and integrates the new 150-ms window. We chose the window's width to be long enough to include the time duration of extended abnormal QRS complexes, but short enough so that it does not overlap both a QRS complex and a T wave. Adaptive amplitude thresholds applied to the band pass-filtered waveform and to the moving integration waveform are based on continuously updated estimates of the peak signal level and the peak noise. After preliminary detection by the adaptive thresholds, decision processes make the final determination as to whether or not a detected event was a QRS complex. A measurement algorithm calculates the QRS duration as each QRS complex is detected. Thus, two waveform features are available for subsequent arrhythmia analysis—RR interval and QRS duration.

We have obtained the followingwaveforms

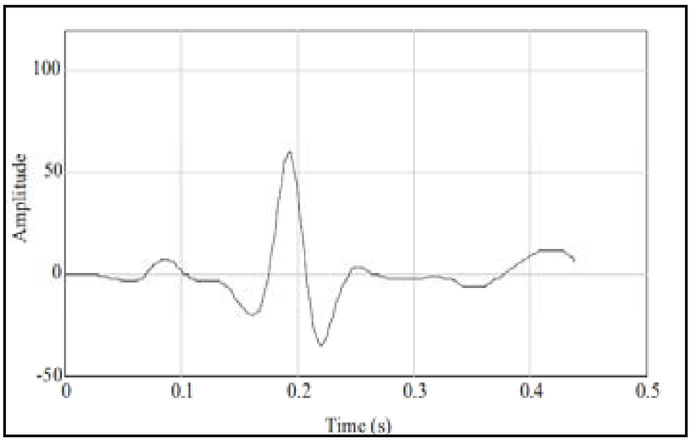
1. ECG Sampled at 200 Samples Per Second



2. Low Pass Filtered ECG

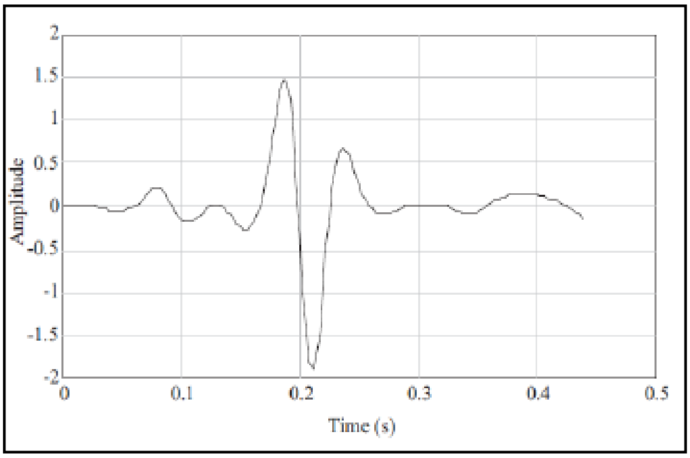


3. Band pass filtered ECG

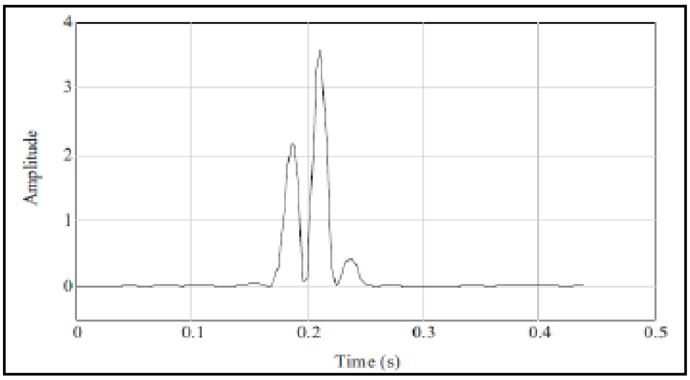


ISSN : 0976-8491 (Online) | ISSN : 2229-4333 (Print)

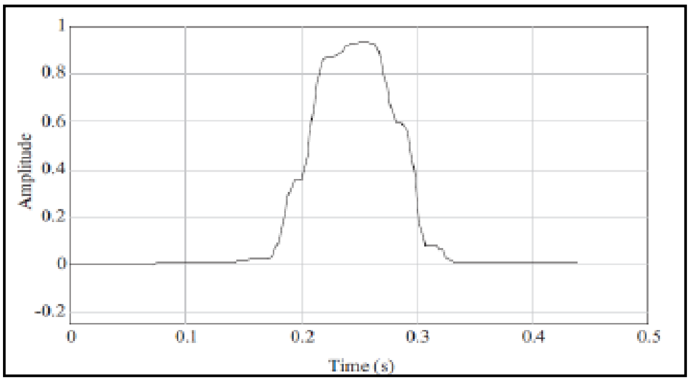
4. Band pass and differentiation



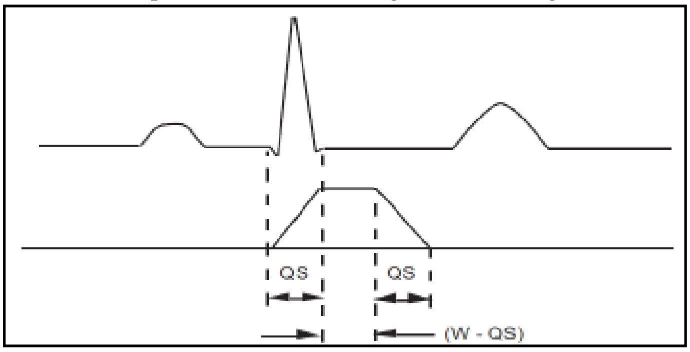
5. Squared waveform



6. Window Integrator



7. Relationship of QRS With Moving Window Integrator



V. Conclusion

We have developed a real time algorithm for detection of QRS complexes of ECG signals. It reliably recognizes QRS complexes of ECG signals. Although the quantitative ECG is superior to its conventional counterpart but the former is yet to be accepted in clinical practice in India. An attempt has been made to develop quantitative ECG acquisition and classification system. We have tested two ECG signals using MATLAB.Corresponding to first ECG signal our program has given heart rate 73 beats per minute, indicating that person is notsuffering from any heart diseases.
Corresponding to second ECG signalheart rate is above the normal that is 207 beats per second, therefore the person is suffering from traccardia.
There is a lot of scope for research work in this field and this type of software can be used at military sites, remote areas, even for homecare systems.

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