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COMPARATIVE ANALYSIS OF VARIOUS QRS TECHNIQUES IN ECG

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Abstract: Detection associated with QRS complexes within ECG alerts is employed in order to characterize heart rate in the entire body. Basically low and high frequency noise affects the ECG signal. Several methods have been used to detect the characteristic pattern of QRS complex and filter out the noise in order to improve the accuracy of the QRS detectors. This research work mainly focus on providing better performance in heart beat detection algorithm by using control parallelism and also by improving MaMeMi filter using the first order derivation. The overall objective of this dissertation is to divide the QRS detection in such a way that each stage of QRS detection can be run concurrently on given set of processors.

Keywords: QRS detection, Real-time systems, nonlinear filter, parallelism, parallel computing.

1. INTRODUCTION

1.1 QRS

The QRS complex is the combination of the graphical deflections observed on a typical electrocardiogram (EKG or ECG). It is usually the central and most visually obvious part of the tracing. QRS complex is created when the depolarization of the right and left ventricles of the human heart occurs. QRS complex normally lasts 0.06–0.10 s in adults; it may be shorter in children and during physical activity. Basically an ECG has five deflections which have been named P, Q, R, S and T. The QRS wave is considered as a unit which is formed during the ventricular depolarization. A Q wave is any negative downward deflection after the P wave. A R wave is any positive deflection after Q and the S wave is any downward deflection after the R wave. The T wave follows the S wave and joins to the QRS complex [1].

1.2 ROLE OF QRS DETECTION

QRS symbolizes the electrical action inside heart over the ventricular depolarization from the heart. The time of the occurrence of QRS complex as well as its shape provide much information about the current state of the heart. The heart rate is determined with the help of QRS complex and is also used in ECG data compression algorithms. Therefore, QRS detection provides the basics for almost all ECG analysis algorithms. In ECG processing it is very important to detect heartbeats accurately, because it is the base for further analysis and can also be used to get information about heart rate. The energy associated within the heartbeats is mainly located in the QRS complex, so an accurate QRS detector is the most important part of ECG analysis. As the beat morphology changes along the time, and different sources of noise can be present therefore QRS detection is difficult. ECG signals are usually affected by several noise sources, like respiration and muscular contraction. Additionally, as a result of a disease or a temporal alteration, heart beats can have very different characteristic behaviors [2].

2. QRS DETECTION TECHNIQUE

2.1 APPROACHES BASED ON SIGNAL DERIVATIVES AND DIGITAL FILTERS

Typically frequency components of a QRS complex range from about 10 Hz to about 25 Hz. 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 in coupling noise, P-wave, T-wave and baseline drift. Whereas the suppression of in coupling noise is usually done by a low-pass filter, the attenuation of the baseline drift as well as P- and T-wave is accomplished by high-pass filtering. The combination of low and high pass means effectively the application of a band pass filter, in this case with cut-off frequencies at about 10 Hz and 25 Hz [3].

2.2 NEURAL NETWORK APPROACHES

Artificial neural networks have been basically used in nonlinear signal processing, classification, and optimization. In many applications their performance was observed to be superior to many other approaches. In ecg signal processing, mostly the learning vector quantization (lvq) , radial basis function (rbf), networks multilayer perceptron (mlp) networks are used .

2.3 WAVELET

An alternative methods based on mathematical tools, known as wavelet transforms, has emerged within the last decades for its possible applications to ECG signal processing Wavelet transforms generate a time-frequency decomposition of the signals, which in turn brings about individual signal frequency components. This decomposition will depend upon the 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. 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 reflect the low frequency components of the signal [4] .

3. LITERATURE SURVEY

Kher *et al.* (2010) [5] has proposed the QRS complex detection algorithms for detection of QRS complexes in ECG based on the first and second derivatives. The derivative based QRS detection algorithms have been effective on variety of ECG database and it is computationally simple also. It delivers results above 98% detection in QRS detection through the modified threshold values.

Shamekhi and sedaaghi (2010) [6] has introduced a novel algorithm for detection of QRS complexes in ECG based on matching pursuit algorithm (MPA).In this algorithm Time-frequency map is used to represent QRS complex. After that the correct regions are detected from the map.The proposed method delivers sensitivity of 99.92% and specificity of 99.85%. The efficiency of the proposed method is detected in the presence of noise and corruption in ECG.

Hendija (2011)[7] has presented the combination of neural network and wavelet match filtering approach in QRS detection. The main focus is put on low computational complexity and low signal-to-noise ratio. It is tested on several signals of MIT/BIH database, we obtained sensitivity above 90% in QRS detection.

Bouabida *et al*. (2011)[8] has proposed a Empirical mode decomposition technique for QRS detection. This method decomposes non stationary and nonlinear signals into the series of signals modulated in amplitude and frequency called intrinsic mode function (IMF).The algorithm is tested on several signals of the MIT/BIH database comprising different pathologies and hence shows results with sensitivity of 78% to 99%.

Wang *et al.* (2011)[9] has presented a novel Dual-Slope QRS detection algorithm which has high accuracy as well as low computational complexity. The width of the QRS complex is in range of 0.06-0.1 sec. The algorithm is based on the fact that change of slope is large at the peak of QRS complex. The hardware requirement is also low. However, this algorithm requires large time for slope computation on both sides of each sample.

Dong (2012)[10] has introduced wavelet transform with extended kalman algorithm. The wavelet transform uses multiresolution technique to decompose and filter the signal of ECG in each scale. QRS wave is determined by the decision rule. But this method is computationally expensive. This algorithm is applied to ECG signal from MIT - BIH database and its performance is measured in terms of sensitivity (Se) and positive predictivity (+P) as 99.34% and 99.28% respectively.

Zhang and Bae (2012) [11] has proposed a very-large-scale integration (VLSI) friendly electrocardiogram (ECG) QRS detector for body sensor networks. Mathematical morphological method is used to remove the Baseline wandering and background noise from original ECG signal. The multipixel modulus accumulation is employed to act as a low-pass filter to improve the signal-to-noise ratio and enhance QRS complex.

Farahabadi *et al.* (2012) [12] has proposed a new algorithm by using a combination of wavelet transform, Hilbert transform and adaptive thresholding.This method is computationally efficient.

Gopeka *et al.* (2014) [13] has presented the very large scale integration (VLSI) based electrocardiogram (ECG) QRS complex detector for wearable devices in body sensor networks. Background noise and baseline wandering from original ECG signal are suppressed by Multiscale Mathematical morphological method. The main benefit of this method is that it does not require any prior knowledge of frequency spectrum. As a result Multiscale Mathematical Morphology is very attractive for noise reduction. QRS detector has an average sensitivity of Se = 97.8% and a positive predictivity P+= 97.8% by evaluating the algorithm on MIT-BIH Database

Arefin and Fazel (2014) [14] has proposed a computationally efficient QRS detection algorithm for wearable electrocardiogram (ECG) applications based on dual-slope analysis. A technique is presented in which two slopes are calculated on both sides of a peak in ECG signal. Using these slopes, steepness is computed and R peaks are detected. Simulated with MIT-BIH Arrhythmia database, the algorithm achieves detection rate of 99.38%.

Ravanshad *et al.* (2014) [15] has introduced an asynchronous analog-to-information conversion system for measuring the RR intervals of the electrocardiogram (ECG) signals. The system consists of a modified level-crossing analog-to-digital converter and a novel algorithm for detecting the R-peaks from the level-crossing sampled data. The algorithm was evaluated against MIT/BIH Arrhythmia database and delivers an average detection accuracy of 98.3%, a sensitivity of 98.89%, and a positive prediction of 99.4%.

Rivas *et al.* (2015)[16] has proposed a real-time QRS complex detector. This algorithm is based on a differentiation at the pre-processing stage followed by a dynamic thresholding to detect R peaks. The thresholding stage is based on a finite-state machine, which changes the threshold value according to the evolution of the signal and the previously detected peak. The proposed system delivers sensitivities and positive predictivities better than 99.3%. As a result, the proposed detector achieves a reduction in processing time of almost 50% by using only the 25% of hardware resources (memory, adders, and multipliers).

Chandrakar and Sharma (2015) [17] has proposed a novel method for detection of QRS complexes in ECG signals. A novel real-time QRS detection technique using two-phase hashing is proposed in this paper. The technique relies more on the data stream corresponding to ECG beats than any particular feature. We use the concept of shared counters to minimize the memory requirement while efficiently shifting through suspicious strings. The algorithm automatically adjusts parameters periodically to adapt to ECG changes as QRS morphology and heart rate. The proposed algorithm correctly detects QRS complexes with negligible false positive and negative detection.

Rufas and Carrabina (2015) [18] has presented the MaMeMi filter, a non-linear high pass filter useful to remove ECG baseline wander. A simple QRS detector based on this filter with minimal resource needs is created. The algorithm is easily implementable both in software and in hardware. The algorithm is tested against the MIT/BIH database achieving detection rate of 99.22%, a sensitivity of 99.43% and a positive prediction of 99.67%.

Falconi *et al.* (2015) [19] has presented an R peak detection algorithm for ECG signals based on the second derivative. These techniques offer low average time error and are computationally inexpensive. However, previously proposed methods based on the second derivatives suffer from low sensitivity and positive predictivity.

4. COMPARISON TABLE

Table 1.comparison of different techniques of QRS detector

REFERENCES	TECHNIQUES	ISSUES	BENEFITS	LIMITATIONS
[9]	Novel dual slope method	Calculate slopes on both sides of a peak	Sensitivity 99.82% Predictivity 99.63%	Time consuming slope calculations
[10]	Waveform method	Decomposes signal of ECG into scales	Sensitivity 99.34% Predictivity 99.28%	Computationally expensive Choice problem of mother wavelet

[16]	Adaptive technique	Differentiation at preprocessing stage Dynamic threshold to detect R peaks	Sensitivity 99.4% Specificity 99.4%	Need complex computations
[14]	Dual slope method	Based on two slopes on both sides of peaks	Detection rate 99.38%	Time consuming slope calculations
[15]	Level crossing method	Detect R peaks from level –crossed sampled data in a compressed volume of data	Sensitivity 98.89% Predictivity 99.4%	Due to absence of filter ,noise is detected as beat
[2]	Higher order statistics	Uses fourth order central moment to detect R peak	Sensitivity 99.43% Predictivity 99.94%	Computationally expensive
[8]	Empirical mode decomposition	Decomposes non-linear and non stationary signals adaptively in a series of signals	Sensitivity 78% to 99%	Difficult to decompose the signal
[11]	VLSI slope method	Multiscale mathematical morphology	Predictivity 97.8% Sensitivity 97.8%	Time consuming morphological operations Detection rate is not high

5. CONCLUSION AND FUTURE WORK

QRS represents the electrical activity within the heart during the ventricular depolarization of the heart. The time of the occurrence of QRS complex as well as its shape provide much information about the current state of the heart. The review has shown that the only low pass and high pass filter are considered. The use of the linear prediction is also ignored. The use of first derivative is not considered in MaMEMi QRS detection. Therefore in near future Butterworth filter, first derivation based upon MaMeMi filter for QRS detection will be proposed. The control parallelism will also be used in order to improve the speed of the proposed technique.

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