QRS Detection using Wavelet Transform

Gaurav Jaswal, Rajan Parmar, Amit Kaul

Abstract— ***The paper has been inspired by the need to find an efficient method for QRS detection which is simple and has good accuracy and less computation time. Our heart acts as the representative of the physiological changes of our body. Electrocardiography (ECG) is the electrical signature of the heart and thus one of the important indicators of our pathological condition. ~~I~~n this paper the Discrete Wavelet Transform is used to detect QRS complex. The DWT approach is found to be better and more accurate than the other common methods when evaluated on MIT/BIH ECG database and the database borrowed from NIT Jalandhar.***

Index Terms— ***Mean square error, QRS, DWT, ECG***

I. INTRODUCTION

Probably the most reliable and oldest available tool for measuring electrical activity of the heart is Electrocardiography or more commonly known as ECG. Electrocardiogram (ECG) introduced into clinical practice more than 100 years ago constitutes a graphical recording of the heart's electrical activity that occurs successively over time. The ECG results determine whether the heart is performing normally or suffering from abnormalities. The recorded ECG is the representation of the depolarization and re-polarization of the heart and can diagnose a patient by looking at the characteristics of the traced ECG readings. There are 3 main deflections in an ECG: the P-wave, the QRS complex, and the T-wave. The first upright wave is called the P wave and is normally round in shape and its duration is usually not more than 0.1 second. The QRS complex corresponds to ventricular depolarization. It is normally 0.04 - 0.12 second in duration. Between the P wave and the QRS complex is the PR interval. It represents the time taken by the SA node electrical impulse to travel from its exit out of the SA node to the beginning of ventricular excitation. It is normally 0.1 - 0.2 second in duration. The T wave is another rounded upright wave corresponding to repolarization of the ventricles. Finally, the ST segment is the electric line between the end of the QRS complex and the beginning of the T wave. Additionally, it is useful for epidemiologic studies and screening [1]. The ECG waveforms may differ for the same patient to such extend that they are unlike to each other and at the same time alike for different types of beats. The

Wavelets are a powerful tool for the representation and analysis of such physiologic waveforms because a wavelet has finite duration as contrast to Fourier methods based on sinusoids of infinite duration. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions.

II. LITERATURE REVIEW

The wavelet transform has emerged over recent years as the most favored tool by researchers for analyzing problematic signals across a wide variety of areas in science, engineering and medicine. Wavelet transform analysis has now been applied to a wide variety of biomedical signals including: the EMG, EEG, clinical sounds, respiratory patterns, blood pressure trends and Deoxyribonucleic Acid (DNA) sequences and the subject of this paper, the ECG. The references are arranged as they appear in the paper.

A. ECG Timing, Morphology, Distortions and Noise

Producing an algorithm for the detection of the P wave, QRS complex and T wave in an ECG is a difficult problem due to the time varying morphology of the signal subject to physiological conditions and the presence of noise. Recently, a number of wavelet-based techniques have been proposed to detect these features. Senhadji et al (1995) [5] compared the ability of three different wavelets transforms (Daubechies, spline and Morlet) to recognize and describe isolated cardiac beats. Sahambi et al (1997a, 1997b) **[**6], [7] employed a first-order derivative of the Gaussian function as the wavelet for the characterization of ECG waveforms. Improvements to the technique are described in Sahambi et al (1998) [8]. Sivannarayana and Reddy (1999) [9] have proposed the use of both launch points and wavelet extrema to obtain reliable amplitude and duration parameters from the ECG. Other less common methods have also been proposed including neural networks, genetic algorithms and syntactic methods (K¨ohler et al 2002) [10]. Recently, wavelet-based QRS detection methods have been suggested by a variety of groups including Li et al (1995) [11] who proposed a method based on finding the modulus maxima larger than a threshold obtained from the pre-processing of preselected initial beats. In Li et al's method, the threshold is updated during the analysis to obtain a better performance. The algorithm achieves a good performance with a reported sensitivity of 99.90% and positive prediction value of 99.94% when tested on the MIT/BIH database. Shyu et al (2004) [12] have extended the algorithm of Li et al to detect ventricular premature contractions (VPCs). By incorporating a fuzzy neural network, they achieved 99.79% accuracy for VPC classification. Martinez et al (2004) [13] also utilized the algorithm of Li et al applying a dyadic wavelet transform to a robust ECG delineation system which identifies the peaks, onsets and offsets of the QRS complexes, and P and T waves. Kadambe et al (1999**)** [14]

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Have described an algorithm which finds the local maxima of two consecutive dyadic wavelet scales, and compared them in order to classify local maxima produced by R waves and by noise. Kadambe etal reported a sensitivity of 96.84% and a positive predictive value of 95.20% when tested on a limited data set (four 30 min tapes acquired from the American Heart Association (AHA) database). Romero Legarreta et al (2005) [15] have extended the work of Li et al and Kadambe et al, utilizing the continuous wavelet transform. Other work has been undertaken by Park et al (1998) [16] using a wavelet adaptive filter to minimize the distortion of the ST-segment due to baseline wanderings. In a subsequent paper by Park et al (2001) [17], a wavelet interpolation filter (WAF) is described for the removal of motion artefacts in the ST-segment of stress ECGs. A noise reduction method for ECG signals using the dyadic wavelet transform had been proposed by Inoue and Miyazaki (1998) [18] and Tikkanen (1999) [19] had evaluated the performance of different wavelet-based and wavelet packet-based thresholding methods for removing noise from the ECG. More recently, Leman and Marque (2000) [20] have developed a wavelet packet thresholding algorithm for signal denoising algorithm, this time to remove the ECG signal from the electrohysterogram—a signal which represents uterine activity during pregnancy. Nikolaev et al (2001) [21] have suppressed electromyogram (EMG) noise in the ECG using a method incorporating wavelet transform domain Wiener filtering. The method resulted in an improvement in signal-to-noise ratio of more than 10 dB. Sternickel (2002) [22] has developed an automated P-wave detector for Holter monitors which uses multiresolution wavelet transform input to a neural network classifier. M.A Khayer and M.A Haque (2004) [23] developed a wavelet based algorithm to calculate Instantaneous Heart Rate (IHR) and associated parameters of electrocardiogram (ECG). IHR time series is constructed from the R-peaks. Ghaffari, H.Golbayani & M. Ghasemi (2008) [24] present a new viewpoint in ECG detection using Continous Wavelet Transform (CWT) C.Saritha, V.Sukanya & Y.Narasimha Murthy (2008) attempted to generate ECG waveforms by developing a suitable MATLAB simulator and in the second step, using wavelet transform, the ECG signal was denoised by removing the corresponding wavelet coefficients at higher scales. Yuliyan Velchev, Ognian Boumbarov (2008) [25] introduces an algorithm for automatic detection of ECG characteristic components.The training algorithm is Improved Iterative Scaling. G. Umamaheswara Reddy, Prof. M. Muralidhar, S. Varadarajan, (2009) [26] proposed a new thresholding technique, called improved thresholding de-noising method for denoising of ECG signal. It selects the best suitable wavelet function based on DWT at the decomposition level of 5, using mean square error (MSE) and output signal to noise ratio. It retains both the geometrical characteristics of the original ECG signal and variations in the amplitudes of various ECG waveforms effectively. The proposed method is better than traditional wavelet geometrical characteristics of ECG signal.

III. METHODOLOGY

The objective of present work is to produce an algorithm for the detection of the QRS complex and to find out the R-R interval using Haar wavelet. The objective has been divided into following points:-

- Obtaining database of ECG signals to be used for the purpose of QRS detection.
- Detection of QRS complex using wavelet transforms.
- Developing an algorithm to estimate R-R time interval.

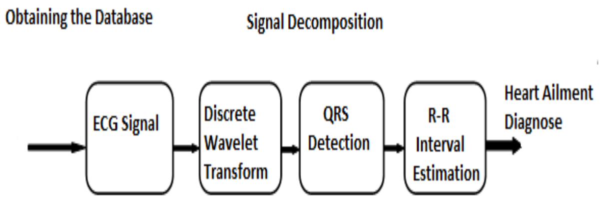

Fig.(a) Block Diagram of the procedure

The rapid and objective measurement of timing intervals of the electrocardiogram (ECG) by automated systems is superior to the subjective assessment of ECG morphology. The timing interval measurements are usually made from the onset to the termination of any component of the ECG, after accurate detection of the QRS complex. The aperiodic, noisy, intermittent, transient signals are the type of signals for which wavelet transforms are particularly useful. Wavelets have special ability to examine signals simultaneously in both time and frequency. We manipulate wavelet in two ways. The first one is translation. We change the central position of the wavelet along the time axis. It is related to the location of the window, as the window is shifted through the signal. This term, obviously, corresponds to time information in the transform domain. However, we do not have a frequency parameter, instead, we have scale parameter which is defined as $1/frequency$. In terms of frequency, low frequencies (high scales) correspond to a global information of a signal (that usually spans the entire signal), whereas high frequencies (low scales) correspond to a detailed information of a hidden pattern in the signal (that usually lasts a relatively short time). Scaling, as a mathematical operation, either dilates or compresses a signal. Larger scales correspond to dilated (or stretched out) signals and small scales correspond to compressed signals. The discrete wavelet transform is viewed as sampled version of the continuous parameter wavelet transform. However theory of discrete wavelet transform can be studied independent of its continuous counterpart. In discrete wavelet transform, we have to deal with basically two sets of functions-scaling functions and wavelet functions. Normalization of reference signal is done so that its maximum and minimum values are equal +1 and -1 respectively, and projection of discrete samples of a “smooth” transform of orthogonal transformations (parallel to argument’s axis) on a normalized reference signal. Wavelet analysis represents a signal using approximation coefficients and detail coefficients. A zero crossing in the detail coefficients usually corresponds to a peak in the input signal. Although a wide variety of wavelets are available, not all are appropriate for wavelet-based peak detection. This work uses the haar wavelet to perform wavelet based peak detection. Multiresolution analysis is useful for identifying peaks of noisy signals. This method makes wavelet-based peak detection more accurate and robust than threshold or curve-fitting-based peak detection methods. Signals usually contain both low-frequency components and high-frequency components.

Low-frequency components vary slowly with time and require fine frequency resolution but coarse time resolution. High-frequency components vary quickly with time and require fine time resolution but coarse frequency resolution. Therefore, a multiresolution analysis method is useful for analyzing a signal that contains both low-and high-frequency components. The multiresolution analysis method can help you recognize both the long-term trend and short-term variations of a signal. Information on the coarser resolution of a signal can help to locate the features, such as peaks, in which we are interested. Observation of the finer resolution levels can refine the gross features and provide more details. We can determine an appropriate level of wavelet transforms to find the peaks or valleys in an input signal. For noise-free data, a small level value is sufficient. For noisy data, we might need a large level value. When we use a large level value, we first need to check if the resulting peak location and amplitudes at that level are what we expect. The wavelet transform level affects the number and location of the peaks in a signal. We can reduce noise or discard insignificant peaks by using a large level value. On the same pattern the Q-point and S-point are detected. The maximum points of DWT corresponds to S-points in the input signal and the minimum points of DWT corresponds to the Q-points in the input signal.

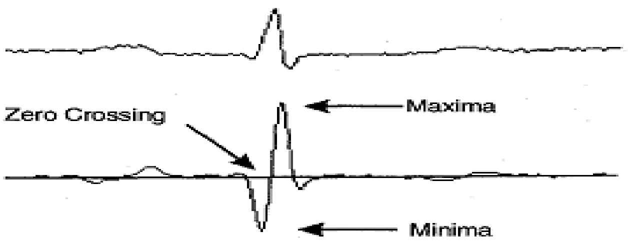

Fig.(b) High frequency component

IV. RESULT & DISCUSSION

In this paper the QRS complex was detected using DWT and the approach was then compared with the “So and Chan” method which is based on the maximum slope detection with the QRS onset selected when two successive values of the slope exceed the threshold. The ECG data files were used to test these two QRS detection methods. Our results showed that the “DWT” method performs better than the “So and Chan” method. Further development continues on the “DWT” method. Based on the information of the identified QRS complexes, the P waves and the T waves can also be detected.

A. The DWT Approach

The ECG signal was taken. One such signal is plotted below. The signal has 7200 samples.

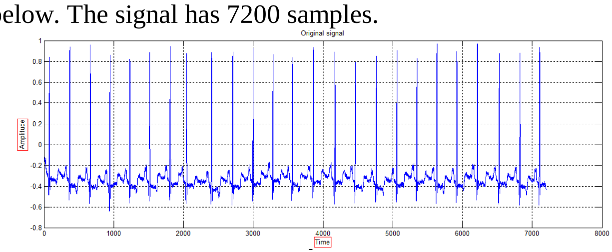

Fig. (c) Original ECG Signal

As it is suffering from baseline drift, therefore smoothing function was required to remove it. The ECG signal after baseline drift elimination is plotted below.

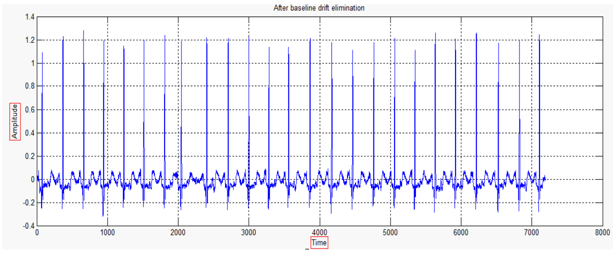

Fig. (d)After baseline drift elimination

The discrete wavelet transform was used to analyze the ECG signal. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, was found to yield a fast computation of wavelet transfor.m. The second level discrete wavelet transform of the signal is plotted below.

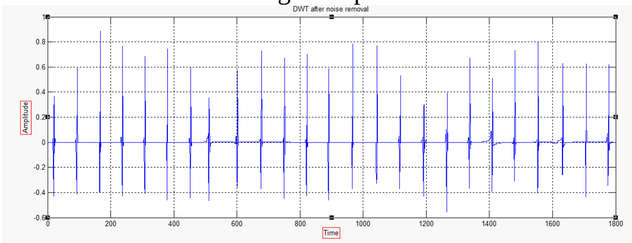

Fig. (e) Discrete wavelet transform after noise removal

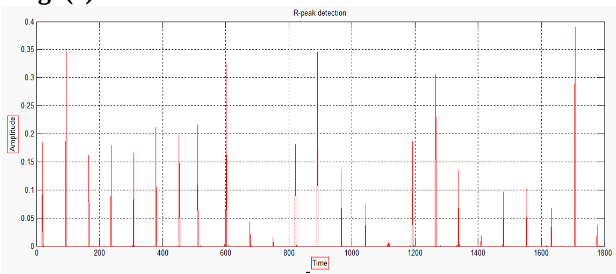

Fig. (f) The R-peak detection

The zero crossings of DWT corresponded to the peaks of original ECG signal as shown in fig. 4.4. and the maxima points and minima points corresponded to the S-points and Q-points of original ECG signal respectively as shown in fig. 4.5 for single cardiac cycle and fig. 4.6 for many cardiac cycles.

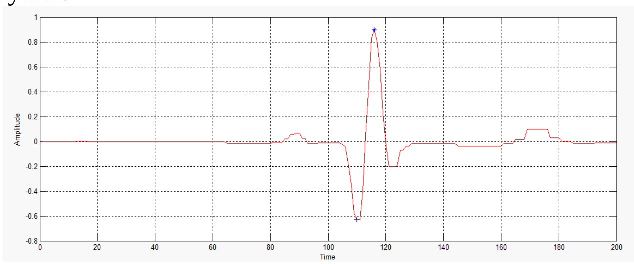

Fig. (g) The first level DWT of single cardiac cycle of ECG signal

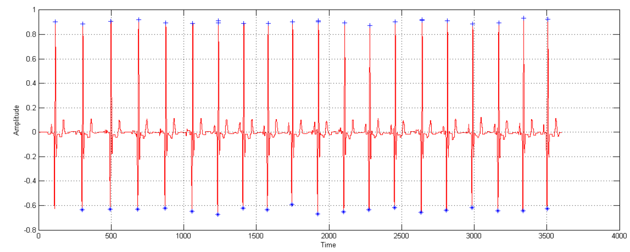

Fig. (h) The first level DWT of ECG having many cardiac cycles

The heart rate can also be found out using the algorithm and for the given subject it was 73. By knowing the heart rate the average R-R time in seconds can be find out as 60/heart rate which came out to 0.81321 seconds as shown in fig. 4.7.

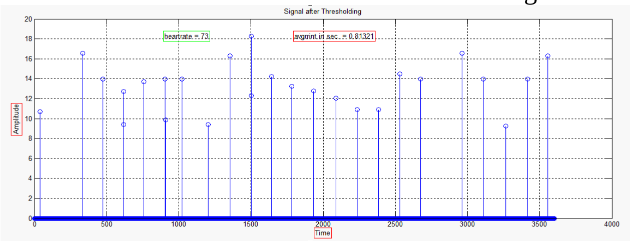

Fig. (i) The heart rate calculation and the average R-R time interval calculation

B. The "So and Chan" Method

The "So and Chan" QRS detection method is intended to implement on the ambulatory ECG monitor. Therefore the first derivative approach was selected. The results are shown in fig 4.8.

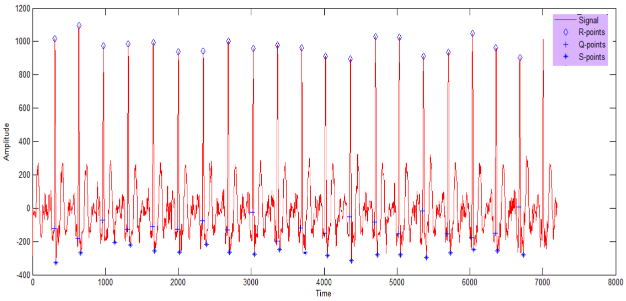

Fig. (j) The QRS complex detection using "So and Chan" method

V. PERFORMANCE EVALUATION AND COMPARISON

The usage of QRS detection algorithms in medical devices requires the evaluation of the detection performance. Essentially two parameters should be used to evaluate the algorithms; that is, the effectiveness of the algorithm can also be evaluated by another parameter called the accuracy. The accuracy of QRS Detection using the DWT approach and the "So and Chan" method is shown in the following table 1.

Table1. Results of QRS detection of the used algorithm (DWT)

ECG Record	Beats Analyzed	False Positives	False Negatives	Detection Failed	Accuracy (%)
Subject 1	20	0	0	0	100
Subject 2	19	0	0	0	100
Subject 3	18	0	0	0	100
Subject 4	21	2	1	3	85.71
Subject 5	16	0	1	1	93.75
Total	94	2	2	4	95.74

The used algorithm (DWT approach) and the "So and Chan" method were implemented using MATLAB 7.10 platform in a computer system having intel core i3 processor with 3 GB RAM.

Table2. Results of QRS detection of the So and Chan method

ECG Record	Beats Analyzed	False Positives	False Negatives	Detection Failed	Accuracy (%)
Sub. 1	20	1	1	2	90
Sub. 2	19	2	0	2	89.47
Sub. 3	18	1	0	1	94.44
Subj. 4	21	1	0	1	95.24
Sub. 5	16	1	0	1	93.75
Total	94	6	1	7	92.55

The elapsed time in milli-seconds for QRS detection using different wavelet family is shown in the following table3.

Table3. Elapsed time in milli-seconds for QRS Detection

ECG Record	Beats Analyzed	False Positives	False Negatives	Detection Failed	Accuracy (%)
Sub. 1	20	1	1	2	90
Sub. 2	19	2	0	2	89.47
Sub. 3	18	1	0	1	94.44
Subj. 4	21	1	0	1	95.24
Sub. 5	16	1	0	1	93.75
Total	94	6	1	7	92.55

VI. CONCLUSION

It can be concluded from the results that discrete wavelet analysis technique can be effectively used for QRS detection. The discrete wavelet analysis technique gives better results than the other conventional methods including "So and Chan" method. Computational time required by DWT approach is very less. Accuracy achieved with DWT is 95.74 % as compared to 92.55 % of "So and Chan" method.

VII. FUTURE SCOPE

Wavelet Transform is a very recent technique. Hence a lot of research needs to be done on the properties so that we can come up with still simpler methods for ECG signal analysis. Feature extraction is yet another field in ECG signal analysis untouched by us. But it is very important for classification of Arrthymia. Hence our future work will be dedicated to feature extraction and classification. The process of enhancement can be modified using more evolved techniques. Research needs to be done for finding more efficient methods for signal enhancement.

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