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WAVELET BASED ECG PEAK DETECTOR

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Abstract

The key indicator of cardiac illness is the electrocardiogram. Lacking of cardiac experts is creating a challenging issue in developing country, especially in Covid situation. Therefore, an expert system required to solve this problem. The presented detector solves this problem by the identification of various peaks of ECG using wavelet transform. Wavelet clearly indicates the frequency and time information of the signal. There are two separate results are presented in the paper about QRS complex and the P, T waves. For QRS complex detection Sym-8 with rigrsure (threshold) gives 99.35% sensitivity. In P and T waves Sym-8 shows 99.65% sensitivity. The comparative analysis of different wavelets also presented. For the purpose of testing the study, the signals from the MIT-BIH's arrhythmia database were employed.

Keywords: - Wavelet, P-wave, QRS Complex, Electrocardiogram, Cardiac Cycle, Arrhythmia

I INTRODUCTION

In modern era, the influence of heart diseases as major contributors to total global death rate has emerged especially in developing countries According to estimates from the World Health Organization, cardiac disorders account for 30% of fatalities. [1]. As a result, the monitoring of ECG signals has grown recently in order to save patient lives by identifying unexpected changes in cardiac circumstances. Identification of QRS complex, P and T wave helps in diagnosis of the patient. There are various techniques available for the identification of waves in ECG, such as wavelet transform, filter bank, genetic algorithms etc. [2].

The ECG reflects the electrical reactions of the heart. The normal ECG's departures from the norm show various cardiovascular conditions. Cardiac cells are electrically polarized in their normal state. Their internal sides are negatively charged with respect to their external sides. Electrodes positioned on the body's surface can sense the electric current flowing over the heart muscle as a result of the depolarization and repolarization of cardiac cells. [3].

Figure 1 illustrates the heart's waveform; P-waves, QRS complexes, and T-wave together make up each beat of heart. The typical heart rate ranges are 60 to 100 beats per minute.

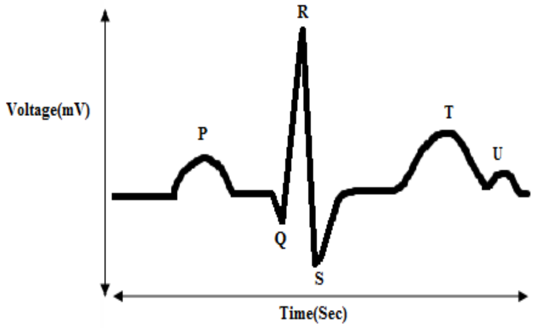


Figure 1 Cardiac Waveform

The dynamic span of an ECG signal is 1-10 mV, and its frequency range is 0.05-100 Hz. The letters P, Q, R, S, and T stand for several waves that typically make up an ECG cycle that represents a single heartbeat. U wave can also be seen in specific situations [5-7]. The P wave typically has a low magnitude (50-100 V) and a 100 m sec duration. The action potential of the Sinoatrial (SA) Node, which circles the atrium, is represented by a P-wave [8]. PR interval results from the conduction between the atria to the ventricles. The QRS complex is produced during the period of ventricular contraction. T waves are produced when the ventricles repolarize [9].

For the automated ECG analysis accurate detection of P, QRS complex and T wave is required. This can be done by different transform such as Fourier, wavelet etcetera. After the identification of QRS complex it can calculate the heart rate, the ST segment and other factors for further analysis [10].

The prior analysis method of ECG was depended on time domain technique. This technique is unable to give frequency related information of different waves of ECG. Therefore; the frequency domain analysis is required. To unravel this, Fast Fourier Transform (FFT) procedure is used. In any case, the unavoidable restriction of this FFT is that the method neglected to give the data with respect to the correct area of frequency segments in time [11]. Since the frequency component of the ECG fluctuates with time, an accurate representation of the ECG recurrence content according to their location in time is crucial. The application of time frequency delineation in quantitative electro cardiology is thus justified. Short Term Fourier Transform (STFT) provides a solution for this purpose. It provides window for the calculation of time and frequency analysis simultaneously [12]. The limitation of this technique is its fixed window size. This problem can be solved by, the wavelet transformation which provides the variable size of window for different time and frequency levels. In Wavelet analysis the relation of frequency and scale are inversely proportional to each other; so at low scale it provides high frequency information and at high scale it gives low frequency information [13-27].

A wavelet is an oscillation that resembles a wave and has amplitude that starts at zero, grows, and then lowers back to zero. The wavelet consist basic wavelets known as mother wavelet and its scaled translated copies are known as daughter wavelet. It decomposes the signal into different levels of frequency and with the help of wavelet coefficient; it provides data for the processing of signal [28-39].

The database of ECG records is created by Boston's Beth Israel Hospital, and at MIT, research on arrhythmia analysis has begun. The researcher can now access it for free on a website [40].

II METHODOLOGY

Figure 2 displays the block diagram for the ECG peak detector.

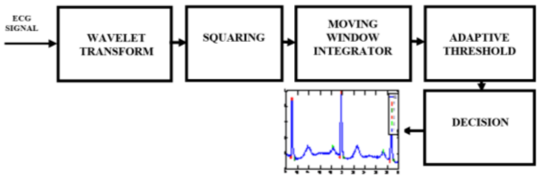


Figure 2 ECG Peak Detectors

ECG Signal

First, a MATLAB executable-formatted ECG record was obtained from the MIT-BIH arrhythmia database. The length of this file for the study project is one minute. Figure 3 displays the original ECG, which has the MIT-BIH database record number 101m.

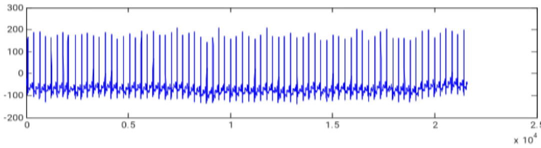


Figure 3 Patient's ECG Signal

Base Line Correction - For base line correction, the selected ECG record, which is a record from the MIT-BIH arrhythmia database, is used. Base-line drift is major hurdle in ECG signal for the detection of QRS complex. The base line drift occurs occasionally with changes in electrode impedance, vigorous movement, or breathing [20]. Equation 1 [6] was used to adjust for baseline errors.

$$ECGsignal = ECGsignal - mean\ (ECGsignal) \ldots\ldots\ldots 1$$

The graphical plot of base line correction is shown in figure 4.

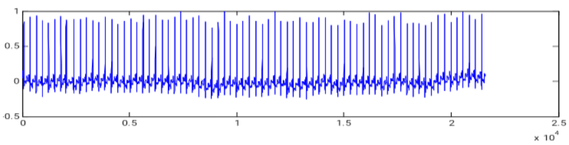


Figure 4 Output of Base Line Correction

Wavelet transforms - When a signal's frequency varies over time, wavelet transforms provide a mathematical method for undertaking signal analysis. The four steps of wavelet denoising are [4]:

1. Denoising
2. Decomposition
3. Threshold
4. Reconstruction

The third & fifth level of denoising is applied on the signal so that it is free from noise like Electromyogram and Power line interference. The distinction of this level has been taken for further examination because it contains QRS complex. The output of this block is demonstrated in the figure 5.

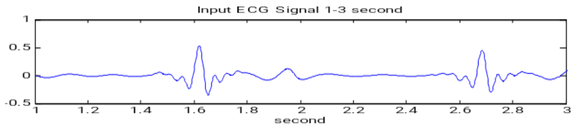


Figure 5 Output of Wavelet Transform

Squaring- Due to the signal's incremented amplitude, this process turns every value of the signal positive and strains the QRS complex. The output is displayed in figure 6.

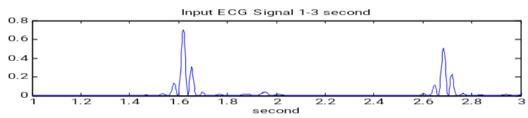


Figure 6 Output of Squaring

Moving Average Integrator- A Moving average integrator removes the various peaks which are present in the period of a single QRS. It takes an average of N samples, where the window width is N=30 and sampling frequency is 360Hz. This operation is performed by FIR filter. It is also called moving window integrator. The output of this block is displayed in Figure 7.

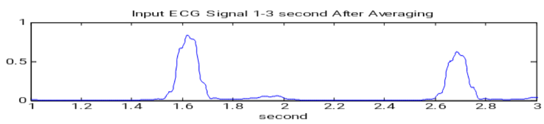


Figure 7 Output of Moving Average Integrator

Adaptive Threshold- It removes noise peaks and gives only QRS complex by using thresholds. Threshold contains two sets with two levels which are applied on the waveform coming from the moving average integrator. These equations perform adaptive threshold operation [21]:

When *Peak (i)* is the signal peak

$$Speak\ (i) = 0.125\ Peak\ (i) + 0.875\ Speak\ (i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

When *Peak (i)* is the noise peak

$$Npeak\ (i) = 0.125\ Peak\ (i) + 0.875Npeak\ (i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

$$Threshold\ (i)_1 = Npeak\ (i) + 0.25(Speak\ (i) - Npeak\ (i)) \ldots\ldots\ldots\ldots\ldots\ldots\ldots 4$$

$$Threshold\ (i)_2 = 0.5\ Threshold(i)_1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 5$$

The response of equation 2 to equation 5 for adaptive threshold is described in figure 8.

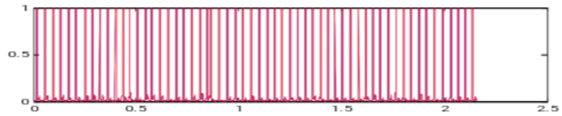


Figure 8 Output of Adaptive threshold

Decision - The peak is referred to as an R-wave if the test signal's assessment value is higher than the threshold level. These are stored in a group, and the group observed the sample number as it appeared in the record. This information provides the QRS complex's R wave's period. To detect the Q and S wave, the algorithm starts searching the minimum point on both sides of the R-peak. Once the minimum point identified, it is located as Q and S point.

Once QRS complex correctly detected by the algorithm then by taking the standard time difference on the horizontal axis P and T-waves are located. The ECG with peaks is displayed in figure 9.

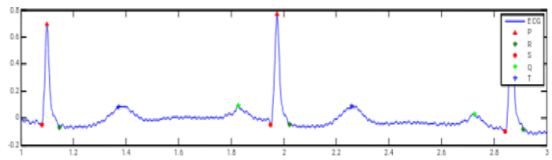


Figure 9 ECG Signal with P, T and QRS Peaks

III RESULT

In the analysis of ECG important step is to precisely distinguish the distinctive waves shaping the whole heart cycle. In order to evaluate the performance of a proposed technique, The MIT-BIH Arrhythmia database's ECG data was imported into the MATLAB environment as a mat file. The algorithm was tested on all forty five records of Arrhythmia database on lead ML2 of MIT-BIH.

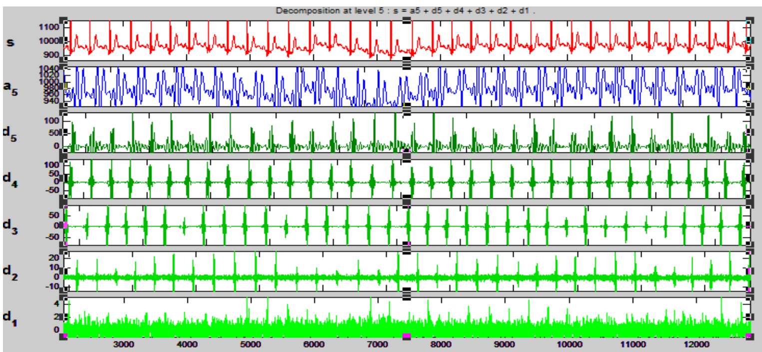
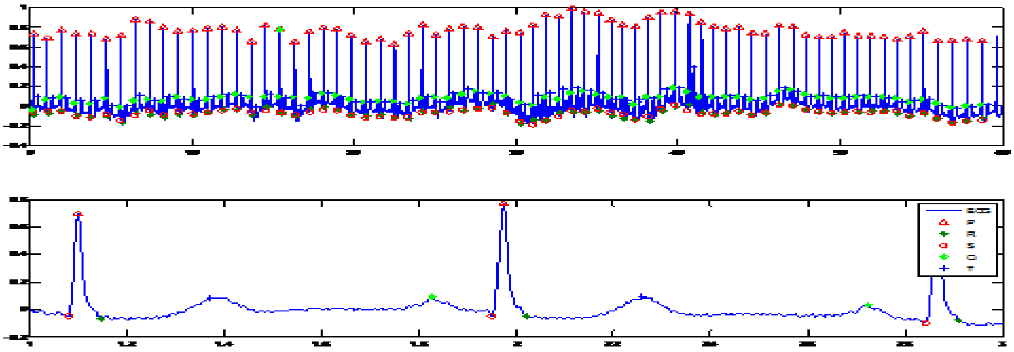


Figure 10 Wavelet Decomposition of ECG Signal

Figure 10 shows the approximation and detail of component of ECG signal using Sym 8 wavelet. The algorithm has capability to recognize the P peak, T peak and QRS complex more precisely as appeared in the Figure 11.



P, QRS and T waves on ECG

Figure 11 Output of ECG Peak Detector

The average test results of different wavelets for forty-five records of MIT-BIH database are tabulated in Table1. The performance was analyzed using the following parameters:-

$$\textit{Sensitivity (\%)} = \frac{T_p}{T_p+F_n}\times 100\% \ldots 6$$

$$\textit{Positive predictive (\%)} = \frac{T_p}{T_p+F_p}\times 100\% 7$$

$$\textit{Detection error rate (\%)} = \frac{F_p+F_n}{\textit{Total count of QRS complex}}\times 100\% \ldots.\ 8$$

Where, T_p = Count of correct beat identified

F_p = Count of false beat identified

F_n = Count of missed target beat

Table 1 *Comparative Analysis of different wavelets*

Wavelet	Results of QRS Complex			Results of P-wave and T-wave		
	Positive Predictivity	**Sensitivity**	**Detection Error**	**Positive Predictivity**	**Sensitivity**	**Detection Error**
dmey	96.96	98.52	4.44	97.69	98.29	3.12
Coief5	95.57	98.08	6.18	95.75	98.88	5.81
Biort55	96.66	98.11	4.95	97.22	97.33	3.59
Rbio6.8	96.86	98.55	4.94	96.68	98.12	4.49
db4	96.72	98.98	4.22	97.27	97.98	2.99
db6	97.45	98.12	4.30	96.54	98.37	4.30
db10	97.10	98.11	4.68	96.11	97.13	4.72
haar	93.77	95.60	10.18	92.52	94.65	11.18
Sym4	97.12	96.96	4.20	96.12	95.25	4.95
Sym8	97.49	98.61	3.82	98.94	99.65	3.02

It has been observed from table 1 that the db4 was given the highest sensitivity of 98.98%, but highest positive predictivity of 97.49% is achieved by sym-8 in QRS complex detection. In P and T wave detection sym-8 was given the highest output with 98.94% positive predictivity and 99.65% sensitivity. The graphical output of detection error is presented in figure 12.

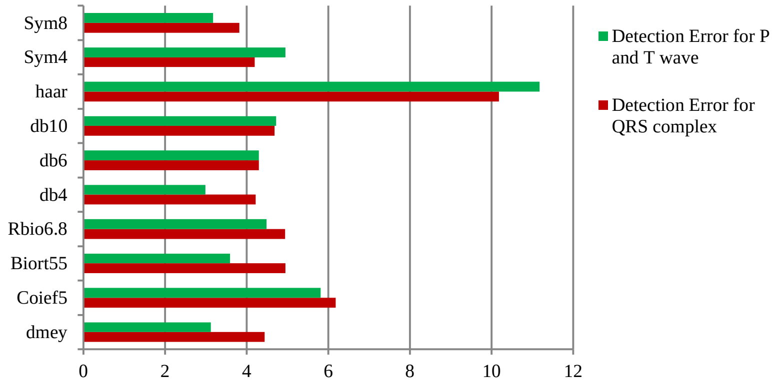


Figure 12 Plot of Detection Error for Wavelets

It has been examined from figure 12 that the low detection error is obtained by symlet-8 for P, T and QRS peak detection. There are four kinds of thresholds (heursure, rigrsure, minimaxi, sqtwolog) in wavelet transformTherefore, determining which threshold display large output is crucial [4]. For this, the program applied the signal using various thresholds, and the outcomes are listed in table 2.

Table 2 *Comparative Analysis of Thresholds*

Thresholds	**Results of QRS Complex**			**Results of P and T Wave**		
	Positive Predictivity	**Sensitivity**	**Detection Error**	**Positive Predictivity**	**Sensitivity**	**Detection Error**
Heursure	97.49	98.61	3.82	98.72	98.84	3.56
Rigrsure	97.49	99.34	3.22	98.94	99.65	3.02
Sqtwolog	97.61	98.62	3.71	98.61	98.26	3.87
Minimaxi	97.67	98.62	3.64	98.69	98.66	3.46

Table 2 indicates that for QRS detection minimaxi provides higher positive predictivity with 97.67%, but higher sensitivity is achieved by rigrsure threshold with 99.34%. In P and T peak detection highest result was obtained by rigrsure threshold with 98.94 % positive predictivity and 99.65% sensitivity. The graphical output of detection error is displayed on figure 13.

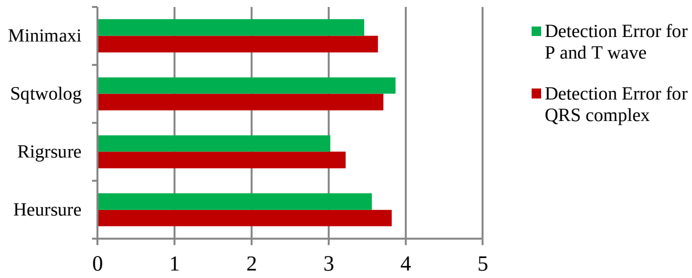


Figure 13 Plot of Detection Error for Thresholds

It has been demonstrated in figure 13 rigrsure threshold provides lowest detection error for P, T and QRS peak.

IV

CONCLUSION

The paper's primary commitment was the designing of wavelet detector for the recognition of the peaks of ECG. Changeable windowing properties of wavelets are a very helpful method to process the ECG. Various basic wavelets (daubechies, symlet and haar etc.) applied on the detector to locate the peaks on ECG. In which highest result was achieved by Symlet-8. Rigrsure threshold shows less detection error as compared to others. Therefore peak detector shows optimal response with Symlet-8 and Rigrsure threshold. The concept of presenting method allows for the examination of other medical signals as well.

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