A Novel Approach of P and T Wave Detection using Wavelets

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***Abstract* — ECG signals are commonly utilized for detection of heart beats and identification of heart abnormalities. An ECG signal primarily consists of three key waveform components: P wave, the QRS complex and T wave. To accurately extract ECG features and detection of P, QRS, T complexes, it is essential to eliminate baseline wander by appropriate Kaiser Windowing filter and minimize the noise interference. This paper proposes and develops an algorithm to detect the QRS complex, P wave and T wave in ECG signals by using wavelet transform. The proposed algorithm achieves detection accuracy 97.8% for QRS complex, 95.5% for P wave is, and 91.7% for T waves. For that we implement an algorithm in MATLAB and tested using standard CSE-ECG database.**

***Index Terms*- Baseline wander, ECG, Kaiser Window, QRS Complex, P Wave, T Wave, Wavelets.**

I. INTRODUCTION

These days heart diseases have become one of the biggest threats in our world, which can be controlled easily but with pre-diagnosis with different clinically significant ECG features. ECG which is the electrical exposition of contractile intercourse of the heart. In normal condition cardiac cells are in electrical polarization i.e. cells' inner sides are negatively charged relative to their outer side. During depolarization the cardiac cells miss out on their negativity and gain a wave by spreading depolarization from cell to cell. which produces electric activity and generates a current flow and detected by the surface of the body by several electrodes. After completion of depolarization the cells again come to their previous normal polarization condition, and it is also detected by electrode [1][2]. The electrocardiogram contains several peaks named P, Q, R, S, T and U and those are shown in Fig.1, is an ideal waveform of ECG [3][4]. The ECG signal is shown in fig.1. have the information of P-wave, PR-interval, PR-segment, QRS complex, ST-segment, ST- interval and T-wave. The P wave represents atrial depolarization, the QRS-complex represents left ventricular depolarization, and the T-wave represents the left ventricular depolarization [16 Nilesh]. P wave depicts atrial depolarization, and ventricular depolarization is depicted by QRS complex. Where T wave depicts ventricular repolarization [5][6][7]. The human electrocardiogram has a frequency range of 0.05Hz-150Hz but useful information presents in 0.05Hz to 45Hz. So, by detecting R-peak localization we can extract the features of electrocardiogram. But ECG signal various noises like baseline drift, motion

artifacts, EMG from the chest wall, instrumentation noise, muscle noise, electrosurgical noise, disturbances due to power supply variations in the device, interference of RF signal etc. also present [8]. So, on first step to remove the Noice by using filtering process without any effect with the original ECG signal. So, R peak detection is considered as the starting point of analyzing an ECG signal. With respect to detected R peak positions, other ECG components wave peaks localization, and their features can be detected. Then from detected R peaks locations, heart rate can be estimated. Slower heart rate (i.e. less than 60 beats per second) may lead to bradycardia, whereas faster heart rate (greater than 100 beats per second) may lead to tachycardia. Wavelet is a powerful multiresolution tool which analyzes a signal at different frequencies into different resolutions. It means that it represents the same signal corresponding to all different frequency bands. Discrete wavelet is very useful with different filters and different cut-off frequencies to measure the signal at different scale factors. The allotment of details information for a signal can adjust by filter operation. Scale is adjusted by up-sampling and down-sampling transference.

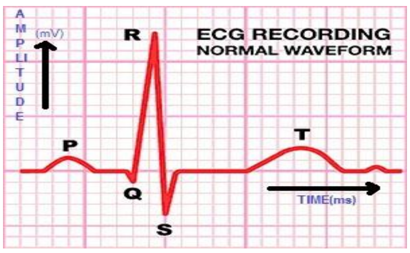

Fig. 1 Normal ECG waveform

II. ANALYSIS METHOD

In this paper we use discrete wavelet transform for detection of the R peaks from ECG wave after the noise filtration process is performed. To extract the information of ECG signal, the raw ECG data signal processed into two stages by functionality of Preprocessing & Feature Extraction as shown in Fig.2

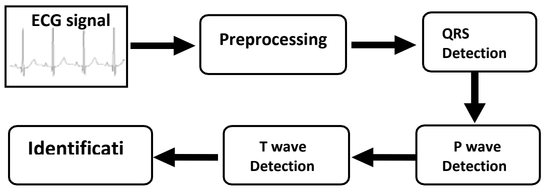

Fig 2: Block Diagram of Analysis Method

A. Pre-processing

In ECG signals one of the commonest problems in ECG signal processing is baseline wander removal and noise suppression. In the ECG signals mainly, noise is present in different types, namely frequency interference, baseline drift, electrode contact noise, polarization noise, muscle noise, internal amplifier noise.

B. Baseline Drift Removal

For removal of baseline drifts without any corruption of the R-waves the first order differentiation of filtered ECG signal is taken to remove motion interference and baseline drifts. The main function of first order differentiation is to indicate high slope points which show that the rising of signal from Q to R is the maximum slope and the falling of signal from R to S is the minimum slope of ECG signal. Therefore, R peak is identified as the zero crossing between these two positive and negative peaks. [10]

C. Moving Average Integrator

An algorithm is implemented in MATLAB For the detection of QRS complex to accurate analysis of ECG signals. In this first, to attenuate noise, the signal passes through a Kaiser Window band pass filter. Then pass through the differentiation, followed by squaring, and moving window integration. After this we found that information of QRS complex is obtained in the derivative stage **[20].** The squaring process gives the maximum slope of the frequency response derived from the differentiation stage, thereby amplifying high frequency while suppressing noise and reduced false positives caused by the T waves. Now the moving window integrator produces a signal that has information regarding both the slope and the duration of the QRS complexes. Its primary purpose of moving-window integration is to extract important features information of the wave form, including the slope of the R wave. Usually, the window width (duration) is set to match the widest QRS complex. But if the window is wide, the integration waveform gives both QRS and T complexes information. If it is narrow, then some QRS complexes will produce several peaks in the integration waveform. This can cause difficulty in subsequent QRS detection processes. So, ideally the QRS complex has a distinct peak in the integrated signal, with the time duration of the rising edge is equal to the width of the QRS complex [11].

So, this algorithm performs accurately to detect QRS complexes using slope, amplitude and width information. Also This algorithm is to adjusts each threshold and RR interval limit from time to time and this compatible approach is allows for accurate use of ECG signals, even with diverse signal characteristics, different QRS shapes and heart rate changes [12]. Compared to the previous paper our research results are found better as seen in the graphical result below.

D. Wavelets Analysis

Feature extraction was performed using wavelet analysis with the help of MATLAB's "wavelet toolbox". This toolbox allows short time intervals to evaluate higher frequencies and a long-time interval for lower frequencies. The wavelet transform is an efficient method for localization of a signal in both time and frequency domain. It provides a time-scale representation of continuous-time signals.

A continuous wavelet transforms (CWT) of a function $x(t) \in L^2(\Re)$ and a wavelet $\psi(t)$ is defined as [13] Wavelet Transform of a signal f(t) is defined as the sum of overall time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ and is given by,

$$W(a,b) = \int_{-\infty}^{\infty} f(t)\,\Psi_{a,b}(t)\,dt$$

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\Psi^{*}\left(\frac{t-b}{a}\right)$$

Where * denotes complex conjugation and, Ψa,b is a window function called the mother wavelet, 'a ' is a scale factor and 'b ' is a translation factor. Here is a shifted and scaled version of a mother wavelet which is used as a base for wavelet decomposition of the input signal. If the scale parameter is the set of Integral powers of 2, i.e., a = 2 j (j ε z, z is Integer set), then the wavelet is called a dyadic wavelet [12]. The Wavelet Transform at scale 2 j is given by

$$Wf(2^j,\tau) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{\infty} f(t)\,\Psi\left(\frac{t-\tau}{2^j}\right)dt$$

We define local maxima of the Wavelet Transform modulus [13] as: - Let is the Wavelet Transform of a function f (x); 1. We call a local extreme any point x0 such that d(Wf (x)) / dx has a zero crossing at x = x0, when x varies. 2. We call a modulus maximum; any point x0 such that |Wf (x) | < |Wf (x0)| when x belongs to either a right or left neighborhood of x0, and | Wf (x) | ≤ |Wf (x0)| when x belongs to the other side of the neighborhood of x0. 3. A maxima lines is a connected curve in the scale space x where every point is a modulus maxima.

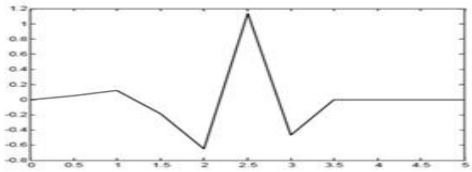

Fig.3. Daubechies db6 wavelet

In Fig. 3 illustrates 3-level signal decomposition of a sample ECG waveform using the db6 wavelet. The ECG signal is initially decomposed into multiple sub bands through the application of Wavelet Transform. Each wavelet coefficient is then changed by using a thresholding method to reduce noise. As low-level details primarily associated with high-frequency components are removed, the overall high-frequency content of the signal is reduced. This process smooths the signal and effectively eliminates noise, particularly around the P and T waves, where such interference is most common due to transmission-induced high-frequency artifacts. [14][18].

III. METHODOLOGY

A. Detection of QRS, P AND T wave

In the Pre-processing stage, noise was removed from the ECG signal by using filtering method. The detection of features was then performed using the Discrete Wavelet Transform (DWT) with dB6 wavelet. This Transform helps to remove noise automatically during signal processing. The results show the ECG signal before and after noise removal. Once the noise was removed, the QRS complex was accurately detected. The R peaks have the largest amplitudes among all the waves, making them the easiest way to detect and good reference points for future detections. The ECG signal was decomposed by using the Daubechies wavelets up to 6 levels. However, for the detection of the QRS complex, only details coefficients up to level 4 were kept and all the rest removed. This step effectively removes low-frequency signals, as QRS waves have higher frequencies than other parts of the ECG [15][16][17].

B. Algorithm for detection

1. Load CSE-ECG database files case by case.
2. Compute a FIR bandpass filter with a Kaiser Windowing technique for removing the various input noise components. The Band Pass filter is designed with cutoff frequency taken as (10 to 40) Hz with the order of N = 07.
3. The baseline drift filtered signal is passed through the differentiator function [diff(x)]. Which computes the differences between successive elements of the filtered output, thereby approximating the derivatives of the signal.
4. After differentiating the output is quite varied and at a low amplitude level. To solve this, the squaring process is done with differentiator output to get the desired level with proper baseline drift.
5. Even after baseline drift and noise reduction, some residual interference can persist. To address this, the ECG signal is further processed using the Daubechies wavelet (db6) with orthogonal properties to improve feature clarity. The ECG waveform will decompose into six levels. Each level contains approximation and detailed information. While detecting the QRS complex, the approximation and detailed information up to the fourth level were kept and the remaining all is removed. So, the detection of QRS complex gives the best results at the fourth level.
6. After detection of QRS complexes the QRS wave amplitude is varying in each case, so the threshold condition is applied to detect and mark the R–wave. Firstly, we find out the maximum peak of the signal after that the condition with 20 percent is applied with the maximum peak of the signal. Then the envelope is put in that position and the average value on that envelope calculated will be R peaks as shown in results.
7. To detect the P wave between two consecutive R - peak the amplitude and time interval threshold condition will be applied. For the amplitude threshold condition, we apply 10 percent of R wave in amplitude level and for time interval the sliding window technique is used in this algorithm with the left side of R peaks. The time interval varies between the values of 100 to 30. In this the maximum peak between the time intervals is found i.e. P wave detection. The graphical results are shown below.
8. To detect the T wave between two consecutive R - peak the amplitude and time interval threshold condition will be applied. For the amplitude threshold condition, we apply 30 percent of R wave in amplitude level and for time interval the sliding window technique is used in this algorithm with the right side of the R peaks. The time interval varies between the values of 30 to 155. In this the maximum peak between the time intervals is found i.e. T wave detection. The graphical results are shown below.

IV. RESULTS

In this study, an algorithm based on Daubechies wavelet transforms was implemented for the detection and characteristics of QRS complex, as well as the detect of P and T wave, using the standard CSE database. It can be noticed that good results obtained with the Daubechies wavelet db6 are caused by the resemblance that exists between this Daubechies wavelet and the actual ECG signal. The results are summarized in the table shows the actual number of QRS complexes (R peaks), number of P and T wave detected, true positive (TP), false negative (FN), and false positive (FP) detection for entire CSE-ECG library dataset-3. Each ECG record of the dataset is of 10 sec durations sampled at 500 samples per second, thus giving 5000 samples. The table also shows the detection rate (DR), positive predictivity (+P) and sensitivity (Se).

FN (false negative): Indicates that the proposed method failed to detect a real beat.

FP (false positive): Indicates that the proposed method detects a beat when no beat is present.

TP (true positive): Stands for the beat, properly detected.

Sensitivity (Se%): This indicates the percentage of true beats that were correctly detected by the algorithm [13, 22].

$$Se\ \% = \frac{TP}{TP+FN} * 100 \qquad \text{... (3.3)}$$

Positive Predictivity (+P%): It gives the percentage of heart beat detection which are reality true beats.

$$+P\ \% = \frac{\mathrm{TP}}{\mathrm{TP+FP}} * 100 \qquad \text{... (3.4)}$$

Detection error rate (DR%): This indicates the percentage of error beats [96].

$$\mathrm{DR}\ \% = \frac{\mathrm{FP+FN}}{\mathrm{TP+FP}} * 100 \qquad \text{... (3.5)}$$

A. *Results in Figure*

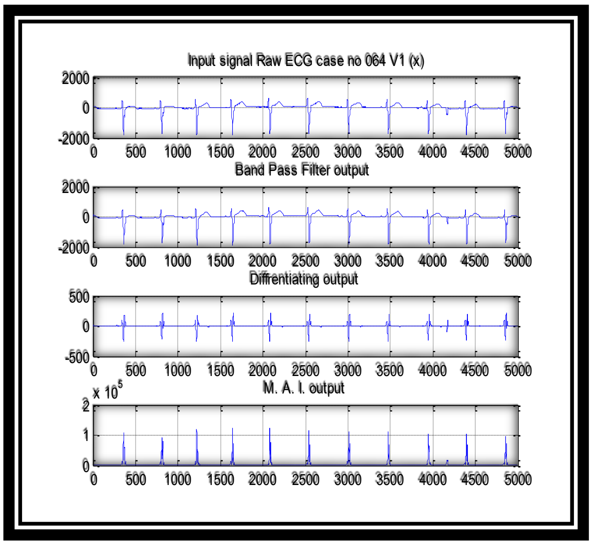

Figure Case no 009 L3 lead Daubechies Wavelet results, R - Peak, P & T wave

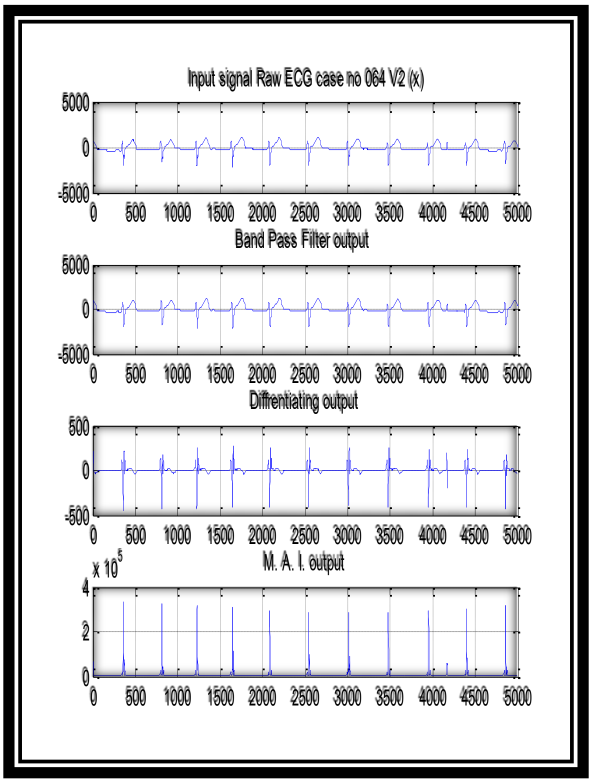

Figure Case no 064 V1 & V2 lead a) Input b) BPF output c) Differentiating output d) MAI output

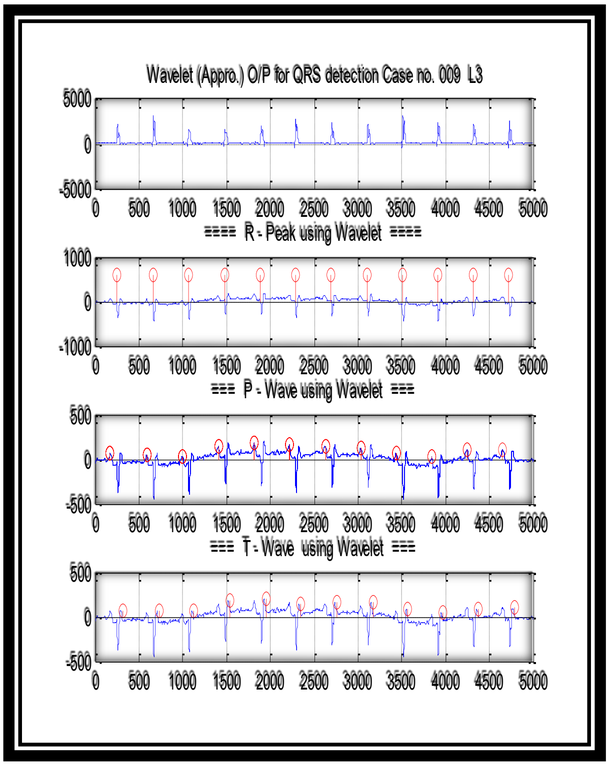

Figure Case no 009 L3 lead Daubechies Wavelet results, R - Peak, P & T wave

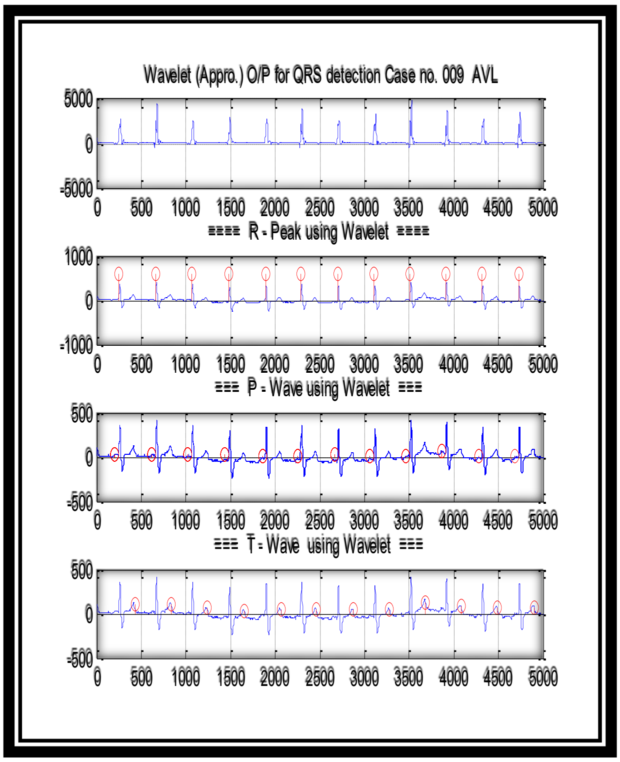

Figure Case no 009 AVL lead Daubechies Wavelet results, R - Peak, P & T wave

B. Results in Tabular form

Table.3.1 Results of QRS wave detection for the entire CSE data base

Table 3.2

Actual no. Of QRS	True Positive TP	False Negative FN	False Positive FP	Detection Error Rate DR	Positive Predictivity +P	Sensitivity Se
17988	17625	363	106	2.60	98.57	97.8

Combine overall results of P wave detection for the entire CSE data base

Actual no. of P	True Positive TP	False Negative FN	False Positive FP	Detection Error Rate DR	Positive Predictivity +P	Sensitivity Se
16301	15339	962	1598	15.7	90.56	95.0

Table 3.3 Combine overall results of T wave detection for the entire CSE data base

Actual no. of T	True Positive TP	False Negative FN	False Positive FP	Detection Error Rate DR	Positive Predictivity +P	Sensitivity Se
17061	15525	1536	925	14.4	94.37	90.94

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