Efficient and low complexity analysis of Bio-signals using continuous Haar wavelet transforms for removing noise

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Abstract:
    This work has been inspired by the need to find an efficient method for ECG Signal Analysis which is simple and has good accuracy and less computation time. The initial task for efficient analysis is the removal of noise. It actually involves the extraction of the required cardiac components by rejecting the background noise. Enhancement of signal is achieved by the use of Empirical Mode Decomposition (EMD) method. The use of EMD was inspired by its adaptive nature. The second task is that of R peak detection which is achieved by the use of Continuous Wavelet Transform (CWT).Efficiency of the method is measured in terms of detection error rate. Various other methods of R peak detection like Hilbert Transform and Difference Operation Method are implemented and the results when compared with the Continuous Wavelet Transform prove that CWT is a better method. The simulation is done in MATLAB environment. The experiments are carried out on MIT-BIH database. The results show that our proposed method is very effective and an efficient method for fast computation of R peak detection.

Keywords: Electrocardiography (ECG), Empirical Mode Decomposition (EMB), Continuous Wavelet Transform CWT), MIT-BIH database.

1.Introduction

1.1   ECG Processing Tasks

   Electrocardiogram (ECG) is a nearly periodic signal that reflects the activity of the heart. A lot of information on the normal and pathological physiology of heart can be obtained from ECG. However, the ECG signals being non-stationary in nature, it is very difficult to visually analyze them. Thus the need is there for computer based methods for ECG signal Analysis. Various signal processing algorithms have been developed to process the electrocardiogram. Detecting QRS complexes in the ECG is one of the most important tasks that need to be performed. This stage is crucial in basic ECG monitoring systems and also is important for all other ECG processing applications. Enhancement of the ECG is also important in a stress test. The stress ECG is prone to various types of noise, and it is important to reduce the noise without distorting the morphology of the ECG. Arrhythmia classification is another important task in interpretive systems which provide a diagnostic classification of the ECG.

Another useful processing task is a noise alert algorithm which determines the fidelity of the ECG by indicating the level and type of noise in the signal

1.2   R wave peak detection

A lot of work has been done in the field of ECG signal Analysis using various approaches and methods. The basic principle of all the methods however involves transformation of ECG signal using different transformation techniques including Fourier Transform, Hilbert Transform, Wavelet transform etc. Physiological signals like ECG are considered to be quasi-periodic in nature. They are of finite duration and non stationary. Hence, a technique like Fourier series (based on sinusoids of infinite duration) is inefficient for ECG. On the other hand, wavelet which is a very recent addition in this field of research, provides a powerful tool for extracting information from such signals. There has been use of both Continuous Wavelet Transform CWT) as well as Discrete Wavelet Transform (DWT). However CWT has some inherent advantages over DWT. Unlike DWT, there is no dyadic frequency jump in CWT. Moreover, high resolution in time-frequency domain is achieved in CWT [3]. Transmission of ECG often results in the corruption of signal due to introduction of noise. [5] Various factors responsible for introduction of noise include poor channel conditions, Baseline wander (caused by respiration), 50 or 60 Hz power line interference etc. Analyzing such a noisy signal is bound to give erroneous results. Thus the signal is first made free of noise, a process called denoising or rather we may call it enhancement. A number of methods have been incorporated for enhancement ECG signal. These include use of filter banks, neural network, adaptive filtering etc. Empirical Mode Decomposition is a recent development which provides a powerful tool for decomposing a signal into a finite number of IMFs (Intrinsic Mode Functions). Empirical Mode Decomposition (EMD) has been used in a number of literatures for R-peak detection as well as enhancement. Fig 1 shows the block diagram of the process incorporated in the proposed method
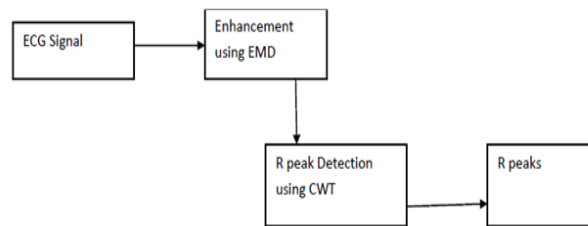

Figure 1. Block diagram of proposed method

1.3   Objective

ECG reflects the state of cardiac heart and hence is like a pointer to the health conditions of a human being. ECG, if properly analyzed, can provide us information regarding various diseases related to heart. However, ECG being a non-stationary signal, the irregularities may not be periodic and may show up at different intervals. Clinical observation of ECG can hence take long hours and can be very tedious. Moreover, visual analysis cannot be relied upon. This calls for computer-based techniques for ECG analysis. Various contributions have been made in literature regarding beat detection and classification of ECG [18] [19] [20].

Most of these use frequency or time domain representation of ECG signals. But the major problem faced by the coders is the vast variations in the morphologies of ECG signals. Moreover, we have to consider the time constraints as well. Thus our basic objective is to come up with a simple method having less computational time without compromising with the efficiency. This objective has motivated us to search and experiment with various techniques. We have implemented enhancement using Empirical Mode Decomposition for its efficiency and we have done the R peak detection using Continuous Wavelet Transform for its efficiency and simplicity. Here using Empirical Mode Decomposition computational time is reduced and efficiency is increased.

Atrioventricu (AV) node	
Bundle of H	
Left bundle Branch	
Right bundle Branch	
Purkinje sys	

2. Materials and Methods

2.1   ECG: anatomical and physiological background Heart:

The heart, located in the mediastinum, is the central structure of the cardiovascular system. It is protected by th bony structures of the sternum anteriorly, the spinal column posteriorly, and the rib cage. Sinoatrial (SA) node is th dominant pacemaker of the heart, located in upper   portion of right atrium. It has an intrinsic rate of 60 100bpm.Atrioventricular (AV) node is a part of AV junctional tissue. It slows conduction,   creating a slight dela before impulses reach ventricles. It has an intrinsic rate of 40–60 bpm [10].

The Heart: Phases: There are two phases of the cardiac cycle [10].

Systole: The ventricles are full of blood and begin to contract. The mitral and tricuspid valves clos (between atria and ventricles). Blood is ejected through the pulmonic and aortic valves.

Diastole: Blood flows into the atria and through the open mitral and tricuspid Valves into the ventricles. Fig. 2 shows conduction system structure. ECG stands for electrocardiography. It is a series of waves an deflections recording the heart's electrical activity from a certain "view". Many views, each called a lead, monito voltage changes between electrodes placed in different positions on the body.
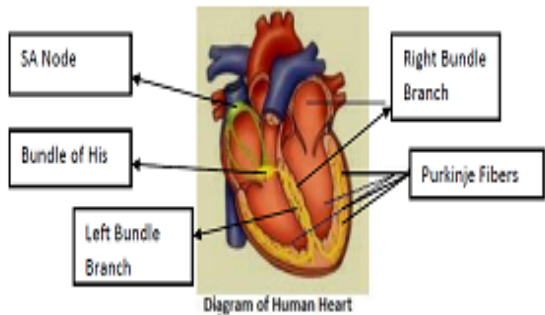

Figure 2.   Conduction system structure

 Each cardiac cell is surrounded by and filled with solutions of Sodium (Na+), Potassium (K+), and Calcium (Ca++). The interior of the cell membrane is considered to be negative with respect to outside during resting conditions. When an electric impulse is generated in the heart, the interior part becomes positive with respect to the exterior.

This change of polarity is called depolarization. After depolarization the cell comes back to its original state. This phenomenon is called repolarization. The ECG records the electrical signal of the heart as the muscle cells depolarize (contract) and repolarize. The Fig. 3 shows the various views of ECG and fig. 4 shows A normal ECG signal.
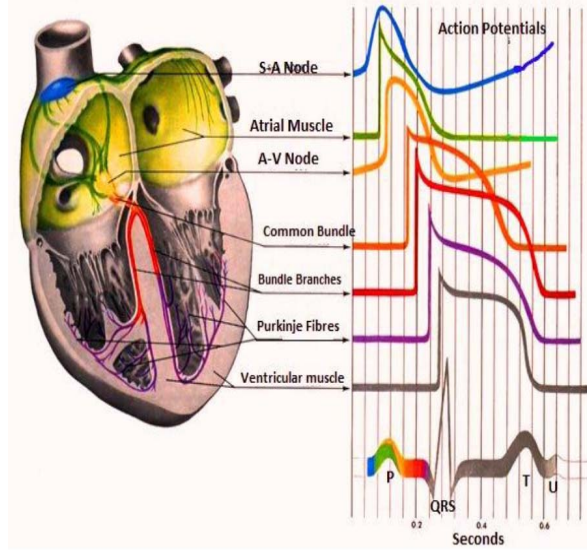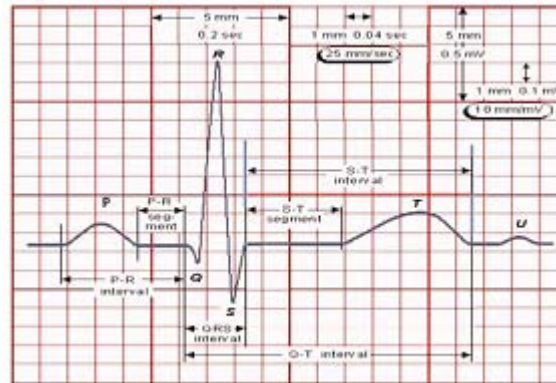
Figure 3.The various views of ECG

Figure 4.   Normal ECG signal and its various components

2.2   P-QRS-T deflections

The impulses of the heart are recorded as waves called P-QRS-T [10].
deflections. The following is the description and significance of each deflection and segment

- *i.*   P wave **:** Indicates atrial depolarization (and contraction).
- *ii.*   PR Interval**:** Measures time during which a depolarization wave travels from the atria to the ventricles.
- iii.   QRS Interval**:** Includes three deflections following P wave which indicates ventricular depolarization (and contraction). Q wave is the first negative deflection while R wave is the first positive deflection. S wave indicates the first negative deflection after R wave.
  ST Segment **:** Measures the time between ventricular depolarization and beginning of repolarization.
- iv   T wave **:** Represents ventricular repolarization.
- v   QT Interval**:** Represents total ventricular activity.

2.3   Arrhytmia

Normally, the SA Node generates the initial electrical impulse and begins the cascade of events that result in a heart-beat. For a normal healthy person the ECG comes off as a nearly periodic signal with depolarization followed by repolarization at equal intervals. However, sometimes this rhythm becomes irregular. Cardiac arrhythmia (also dysrhythmia) is a term for any of a large and heterogeneous group of conditions in which there is abnormal electrical activity in the heart. The heart beat may be too fast or too slow, and may be regular or irregular. Arrthymia comes in varieties. It may be described as a flutter in chest or sometimes "racing heart". The diagnosis of Arrthymia requires Electrocardiogram. By studying ECG, Doctors   can   diagnose the disease and prescribe the required medications.

3. Enhancement of ECG Signal using EMD Method

ECG provides information regarding the state of heart i.e. it gives us useful data regarding diseases. Thus ECG analysis is an important method for monitoring patients. However, the efficiency of diagnosis relies heavily upon accurate analysis of the signal. But the ECG signal that we obtain for analysis is not free from noise. The most important job for a coder is to denoise the ECG i.e. to extract the valid cardiac components and reject the rest of the background noise.

Transmission of ECG often results in the corruption of signal due to introduction of noise [4] [5]. Various factors responsible for introduction of noise include poor channel conditions, Baseline wander (caused by respiration), 50 or 60 Hz power line interference etc. Analyzing such a noisy signal is bound to give erroneous results. The process of extracting the required components while rejecting the background noise is called Enhancement of ECG signal. Numerous methods have been implemented for denoising ECG signals. Some of them are use of Neural Networks [8], Wavelet Transform [9], Independent Component analysis [7] etc. These methods have shown good performance but have some limitations like arbitrary nature, dependence on frequency content etc.

In our search for an efficient enhancement technique, we have implemented a combination of Empirical Mode Decomposition method and low-pass filtering for the enhancement of ECG signal.

3.1   Empirical Mode Decomposition:

A new non-linear technique, called Empirical Mode Decomposition method, has recently been developed by N.E.Huang *et al* for adaptively representing non-stationary signals as sums of zero mean AM-FM components [6]. EMD is an adaptive, high efficient decomposition with which any complicated signal can be decomposed into a finite number of Intrinsic Mode functions (IMFs). The IMFs represent the oscillatory modes embedded in the signal, hence the name Intrinsic Mode Function. The starting point of EMD is to consider oscillations in signals at a very local level. It is applicable to non-linear and non-stationary signal such as ECG signal.

An Intrinsic Mode function is a function that satisfies two conditions [6]:

- The number of extrema and the number of zero crossings must differ by at most 1.

- At any point the mean value of the envelope defined by maxima and the envelope defined by minima must be zero.

Shifting Process

Some of the assumptions made for decomposition are:

- The signal has at least two extrema: one maximum and one minimum

- The characteristic time scale is defined by the time lapse between the extrema.

- If the signal has no extrema but has inflection points, then the signal can be differentiated one or more times to find the extrema.

The basic principle of this method is to identify the intrinsic oscillatory modes by their characteristic time scales in the data empirically and then decompose the data. A systematic way to extract the IMFS is called the Sifting Process and is described below:

- Identify all the extrema of x(t).

- Interpolate between minima, ending up with a signal min (t) and similarly between extrema to give max (t).

- Compute the average: e(t)= (min (t) + max (t))/2

- Extract the detail: d(t) = x(t)-e(t) (Steps 1-4 are repeated till d(t) satisfies both the criteria of IMF)

- Iterate on the residual e(t)

In practice, after a certain number of iterations, the resulting signals do not carry significant physical information. To prevent this, we go for some boundary conditions. We can stop the sifting process by limiting the normalized standard deviation (nstd). [12]

The nstd is defined as :

$$nstd = \sum_{t=1}^{T} \frac{\left(xi(t) - xi(t+1) \right)^2}{\left(xi(t) \right)^2}$$

The nstd is set between 0.2 and 0.3 for proper results. [12]

The sifting process was applied on an ECG signal to obtain the various IMFs.

This has been represented in Fig.5 and Fig.6.

Fig 5. Shows an ECG signal (200_1 MIT-BIH database) containing 1000 samples. Fig.6 shows the various IMF's of the ECG signal given in fig. 5
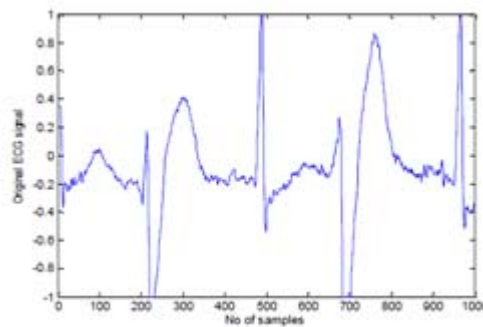

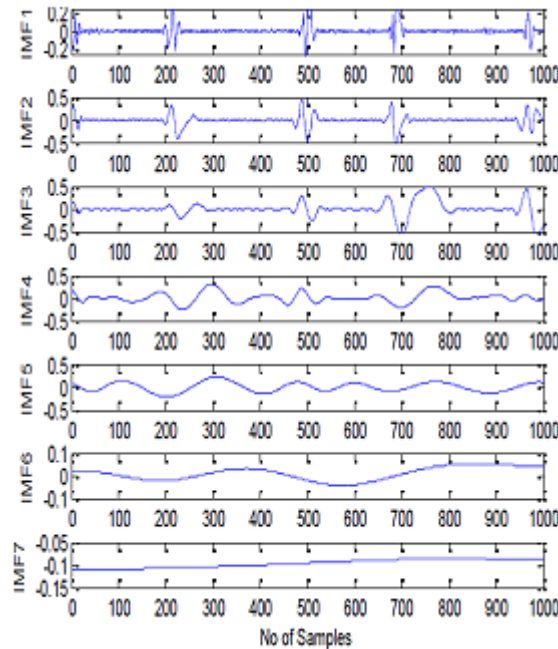Figure.5.ECG signal (200_1 MIT-BIH database) containing 1000 samples

Figure 6.   The various IMF's of the ECG signal given in fig.5

The EMD method is a powerful tool for analyzing ECG signal. It is very reliable as the base functions depend on the signal itself. EMD is very adaptive and avoids diffusion and leakage of signal. The basic principle of enhancement of ECG signal using EMD is expressing the noisy ECG as sum of a series of IMFs. It has been shown that the 1st IMF contains nothing but high frequency noise [4]. So we can easily eliminate this component. The next two IMFs contain both noise as well as information. It has been shown that if we remove the 2nd IMF there is heavy distortion of the R- peaks [4]. In order to remove noise while preserving the information we go for filtering.

The whole procedure can be described by the following algorithm. The ECG signal is first decomposed into IMFs. The sum of these IMFs should represent the signal well. The IMFs are obtained using the sifting process described in the earlier section. The first four IMFs are filtered to remove noise. We use a low pass filter as the noise comprises the higher frequency components. The filter used by us in programming is the low pass Butterworth filter. We use a Butterworth filter because of its inherent characteristics of having a flat frequency response.The 1st IMF is now eliminated. We reconstruct the enhanced signal by eliminating the 1st IMF and adding up the rest IMFs.

4 . R peak Detection of ECG Signal

ECG signal can be expressed as repetitions of P-QRS-T waves. The basic principle behind the analysis of ECG signal is finding the QRS complex. R peak detection is the 1st and foremost step in finding the QRS complex. Various methods have been implemented in the recent past for R peak detection including Fourier Transform, Hilbert Transform [1], Difference Operation Method [2], Wavelet Transform [3], Empirical Mode Decomposition [11] etc. We have tried out a few methods in the course of our search for an efficient algorithm for R peak detection.

4.1   Use of Hilbert Transform for R-peak detection:

Hilbert Transform
        Given a real time function x(t) its Hilbert transform is given by X(t) as

$$X(t) = H[x(t)] = 1/\pi \int_{-\infty}^{+\infty} \frac{x(\tau)}{t-\tau} d\tau \qquad (1)$$

It can be seen from equation 1 that the independent variable is not changed a result of this transformation. So the output F(t) is also a function of t. Moreover F(t) is a linear function of f(t). It is obtained from f(t) by applying convolution with $(\pi t)-1$.

$$X(t)=(1/\pi t) * x(t) \qquad (2)$$

X(t) and x(t) are related to each other in such a way that they together create a strong analytic signal. The strong analytic signal can been written with a amplitude and phase where the derivative of phase can be identified as the instantaneous frequency. The Fourier transform of the strong analytic signal gives us a one sided spectrum in frequency domain.

$$\text{The analytic signal is expressed as } y(t)= x(t) + j\, X(t) \qquad (3)$$

$$\text{The envelope B(t) of y(t) is } B(t)= \sqrt{x(t)^2 + X(t)^2} \qquad (4)$$

And its instantaneous phase angle in the complex plane can be defined by

$$\Phi(t) = \arctan\left(\frac{X(t)}{x(t)}\right) \qquad (5)$$

Applying the fourier transform we have

$$F\{x(t)\} = \frac{1}{\pi} F\left\{\frac{1}{t}\right\} F\{x(t)\}$$

$$= -j\, sgn\, f\, F\{x(t)\} \quad \text{as } F\left\{\frac{1}{t}\right\} = -j\, sgn\, f \qquad (6)$$

Thus we find that a function and its Hilbert transform are orthogonal. Hilbert transform of the original function x(t) represents its harmonic conjugate. The use of Hilbert Transform in ECG signal analysis was first described by Bolton and Westphal. The envelope determined using (4) has the same slope and magnitude of the original signal x(t) at or near its maxima. Moreover B(t) is always a positive function as can be seen from (4). Hence, when x(t)=0, the maximum contribution to B(t) is given by the Hilbert transform. So if we have to find the peaks, i.e. the points where

$$\frac{d}{dt}(ECG) = 0 \qquad (7)$$

 then indirectly we need to find the maximum contribution to the envelope of the first differential of the ECG. This is the basic principle underlying the use of Hilbert Transform in R-peak detection. The Algorithm developed by D. Benitez [2] is described below: Fig. 7 shows the process of finding R peaks using Hilbert transforms.
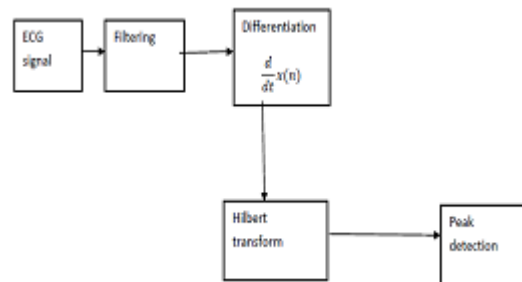

Figure 7. Block diagram of process of finding R peaks using Hilbert transforms

The steps followed can be summarized as follows:
The signal is first filtered to remove noise and enhance the signal. The filtered signal is then differentiated to get the points of minima or maxima. The differentiated signal is then transformed using Hilbert Transform and we determine the envelope by using equation (4). Use of Difference Operation Method for R peak detection

4.2   Difference Operation Method :

Difference Operation is a simple and fast method for   detecting QRS complexes [1]. DOM includes two stages: 1st stage is to find the R peak by applying difference operation to the ECG signal. 2nd stage looks for points Q and S to find the QRS complex. The Difference Operation method doesn't involve any complex mathematical calculation such as cross-correlation, Fourier transform etc. It essentially involves finding the difference signal or the derivative. Thus it uses basic calculus for finding the   peak points. The method of Difference operation is as follows:

- Obtain the difference signal of a given signal x(t) as d(t)= x(t)-x(t-1)
- The difference signal is passed through a low pass filter to obtain df(t)
- Threshold is used for finding the required peak points.

The algorithm for the difference operation method [1] is described below: The difference operation is first implemented according to the following steps:

 • Download the original ECG signal x

 • Obtain the difference signal xd given as xd(n)=x(n)-x(n-1)

 • Pass the difference signal through a low pass filter to obtain xdf

 • xdf is then put through thresholding to obtain xdf 1
R peaks are then detected by following the steps as given below:

 • Separate xdf1 into two kinds of signals: positive and negative parts

 • Select the correct extreme value points

 • The position of maximum positive value is point R in the interval

The process followed for Q and S detection is:

 • Consider 20 points before and after R-peak .The position of minimum value in front of R is Q1 and after R is S1.

 • Consider 80 points before and after R peak. The position of minimum value in front   of   R is Q2 and after R is S2.

 • If pos(Q2)=pos(Q1) then Q=Q1
   If Vq2<Vq1 then Q=Q2
   If Vq2>Vq1 then Q=Q1

 • Similar method is followed for S detection

4.3   Use of Continuous Wavelet Transform in R peak Detection

1.Wavelet Transform: Wavelets are a powerful tool for the representation and analysis of ECG signal. They have been implemented for the analysis of physiological waveforms like ECG, Phonocardiogram etc. [15] [3] [13] [17]. This is because wavelet has finite duration as compared to Fourier methods based on sinusoids of infinite duration. Wavelet Transform involves the decomposition of signal into various components. They provide both time and frequency view. Unlike Fourier transform, they are very efficient for non-stationary signals like ECG.
The Fourier Transform is a widely used tool for many scientific purposes but it is well suited for stationary signals. Gabor introduced a local Fourier analysis. He used the concept of a sliding window. This method, however, gives results when the coherence time is independent of frequency. Morlet introduced Wavelet Transform to have a coherence time proportional to the period. In Wavelet Transform, a fully scalable modulated window is used which solves the signal-cutting problem. The window is shifted along the signal. Spectrum is calculated for every position.

This process is repeated by varying the length of the window. So we have a collection of representations, hence the name multi-resolution analysis.

2. Continuous Wavelet Transform: Wavelet transforms are applied to decompose the signal into a set of coefficients that describe the signal frequency content at given times. The continuous wavelet transform of the signal, x(t), is defined as [3]:

$$F(a,b) = 1/\sqrt{a} \int_{-\infty}^{+\infty} x(t) * \Psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

Here $\Psi(t)$ is the analyzing wavelet function
a is the dilation parameter and
b is the location parameter of the wavelet
 Actually the wavelets are generated from a single basic wavelet $\Psi(t)$, the so called mother wavelet, by scaling and translation.

$$\Psi s,\tau (t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right) \qquad (2)$$

Here τ is the scaling factor and $\sqrt{(1/s)}$ is for normalization across the different scales.
Due to the scaling and translation, Wavelet Transform is localized in both time and frequency. Several Mother Wavelets like Mexican-hat and Morlet have been used in ECG signal analysis. The mother wavelet has a lot of significance for the efficiency of the process. In this paper we have used Haar Wavelet as the mother wavelet. We have gone for Haar wavelet because the oscillatory nature of other mother wavelets results in several ridges for each ECG component, while only one pair of ridges is generated via the Haar wavelet due to its configuration. Fig. 8 shows the Haar wavelet. The Haar wavelet's mother wavelet function $\Psi(t)$ as shown in Fig.8 can be described as

$$\Psi(t) \quad = \; 1 \; 0 \le t < 1/2$$
$$= -1 \; 1/2 \le t < 1$$
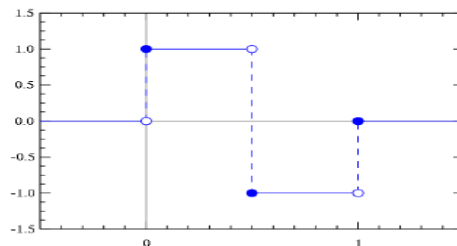$$= \; 0 \; \text{otherwise}$$

Figure 8. Haar mother wavelet

CWT over DWT is choosed because unlike DWT there is no dyadic frequency jump in Continuous wavelet transform [3]. Also high resolution in time-frequency domain is achieved. The basic principle involved here is using a threshold detector [3]. After the enhancement of the ECG signal, it is transformed using Continuous Wavelet Transform using equation (2).

The mother wavelet used here is the Haar Mother wavelet. It is preferred here because the oscillatory nature of other mother wavelets results in several ridges for each ECG component, while only one pair of ridges is generated via the Haar wavelet due to its configuration. The second step involves the use of a Threshold based detector.

Positive maximum peaks larger than a threshold are selected. The main threshold is chosen as a fraction of root mean square of the signal. We have chosen this to be around two times the root mean square of the signal after carrying out a series of experiments.

For further identification of Q and S peaks we use search intervals. Other positive and negative peaks are searched about the R peaks. The positive maximum peak to the left of R peak denotes Q and the negative minimum peak to the right of R peak denotes S.

The search interval is taken as 2.5 times of the scale to the left of R peak and 2 times to the right of it. To avoid misdetection of P and T waves each interval is checked for interference.

5. Experimental Results

MIT-BIH database is used to validate the efficiency of proposed method. Simulation was carried out in MATLAB environment. Addition of White Gaussian noise to the clean ECG signals to obtain a collection of noisy ECG signals with SNR varying from 5 dB to 30 dB is done.

The enhancement algorithm was then used and the SNRs of the enhanced signals were calculated to find the efficiency of the proposed method.

To validate the efficiency of the method, after the process of enhancement, implementation of R peak detection using CWT.

Fig. 9. (a) shows clean ECG signal and 9. (b) and 9. (c) shows noisy ECG signal after the addition of white Gaussian noise and Denoised signal after signal enhancement. Table 1 shows experimental results for Enhanced method using EMD

Fig. 10 shows Step by step representation of each stage in the process of using Hilbert transform and Table 1 shows Experimental results for Enhanced method using EMD
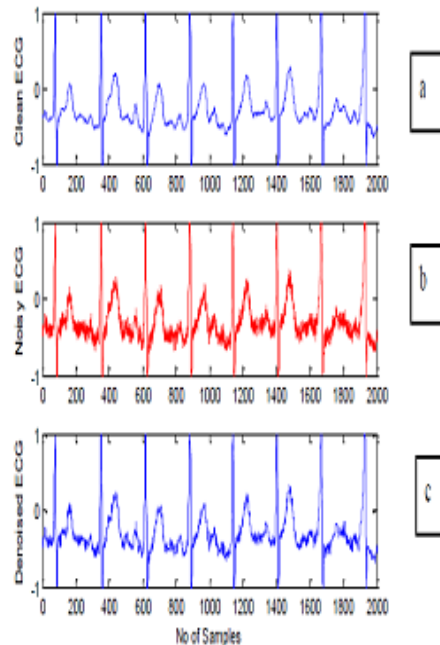

Figure 9. (a) Clean ECG signal (b) Noisy ECG signal after the addition of white Gaussian noise (c) Denoised signal after signal enhancement.

Table 1 Experimental results for Enhanced method using EMD

Noisy signal SNR(dB)	MIT BIH Record	Enhanced Output SNR(dB)
5	200_1	25
	201_1	11.35
	202_1	11
	210_1	7.5
	230_1	19.9
10	200_1	33.5
	201_1	23.56
	202_1	20.5
	210_1	15.39
	230_1	27.89
15	200_1	43
	201_1	31.34
	202_1	28.7
	210_1	23.38
	230_1	32.11
20	200_1	45
	201_1	40.95
	202_1	45.47
	210_1	30.26
	230_1	41
25	200_1	46.05
	201_1	34.1
	202_1	51
	210_1	37
	230_1	42.5
30	200_1	49.46
	201_1	48.97
	202_1	40.9
	210_1	43.2

Table 2 shows experiments of using Hilbert transform for R peak detection

This indicates the detection error rates and sensitivity. Here FP denotes False Positive i.e. False peak detection and FN denotes False Negative i.e. failure to detect.

The total detection error rate is calculated as (FP +FN)/Total no of R peaks *100. The average detection error rate is found to be 0.21%. Efficiency is measured in terms of Sensitivity given by

$$ Se = \frac{TP}{TP + FN} \times 100 $$

Here TP stands for True Positives which is the total no of peaks correctly detected by the detector.

Sensitivity is calculated to be 99.8 % which shows the method has a good efficiency

Although this method is very crude it comes with some   advantages. The unwanted effects of large peaked T and P waves are minimized. Moreover it has been shown to perform extremely well in the presence of noise [2].

Experimental results for Difference operation method

On implementing DOM method as proposed by Yun-Chi Yeh [1], we found the method to be simple, efficient and having less computational time.
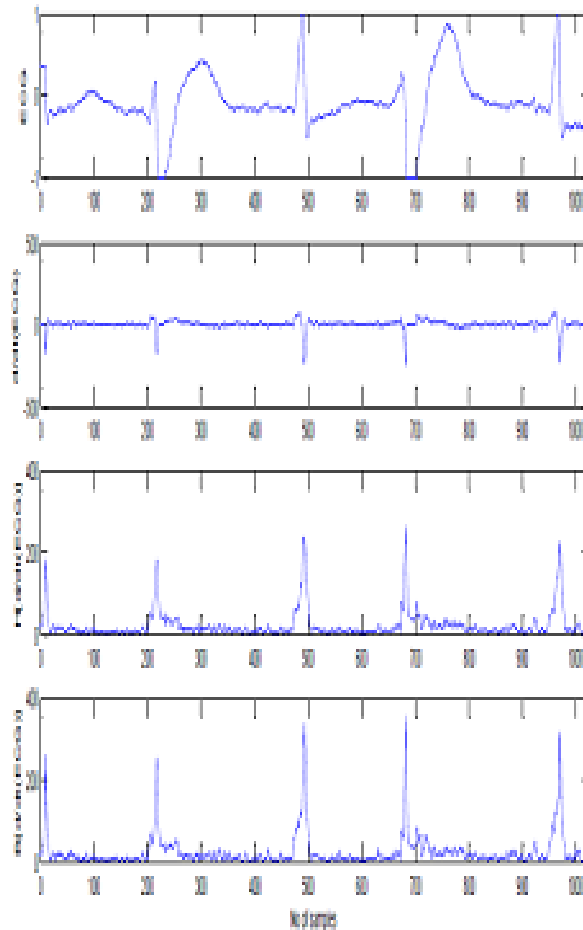
Figure 10. Step by step representation of each stage in the process of using Hilbert transforms

The efficiency was measured in terms of detection error rate i.e. it is a measure of the number of failures.

Simulation was carried out in MATLAB environment. The signals used are from the MIT-BIH database. Fig. 11 shows experimental results for Differential operation method (DOM). This shows Step by step representation of the various stages in the DOM method.

Table 2 *experiments of using Hilbert transform for R peak detection*

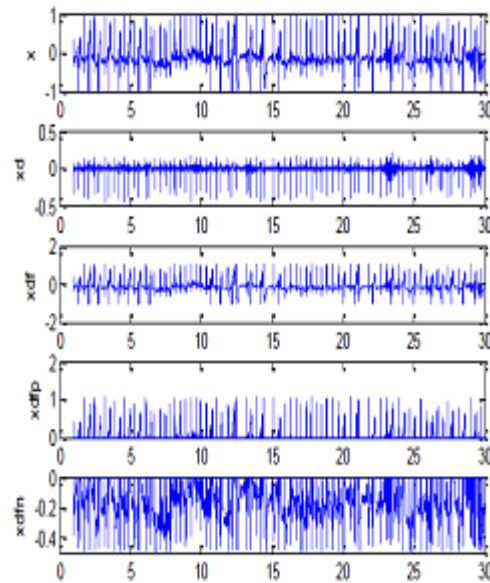| MIT BIH Record	Actual No of Beats	FP	FN	FP+FN	Detection Error rate = $\frac{FP+FN}{Total\ No\ of\ Beats} \times 100$	Sensitivity Se= $\frac{TP}{TP+FN} \times 100$
200	2601	0	0	0	0	100
201	1963	2	7	9	0.45	99.6
202	2136	4	4	8	0.37	99.8
203	2982	6	10	16	0.53	99.6
205	2656	0	7	7	0.26	99.7
208	2956	4	5	9	0.30	99.8
209	3004	0	2	2	0.06	99.9
210	2647	2	4	6	0.22	99.8
212	2748	0	4	4	0.16	99.8
213	3251	2	2	4	0.12	99.9
215	3363	5	0	5	0.15	100
217	2208	0	0	0	0	100
219	2154	0	1	1	0.05	99.9
220	2048	2	0	2	0.09	100
221	2427	1	3	4	0.16	99.9
222	2484	6	15	21	0.84	99.3
223	2605	1	1	1	0.04	99.9
Average	2448.7	2.06	3.82	5.82	0.23	99.8

Figure 11.Step by step representation of the various stages in the DOM method.

Fig. 12 shows R peak and QRS detection using DOM approach: Red lines denote R peaks and QRS complexes. Table 3 indicates the detection error rates and sensitivity. The average detection error rate is found to be 0.21%. Sensitivity is calculated to be 99.94%.
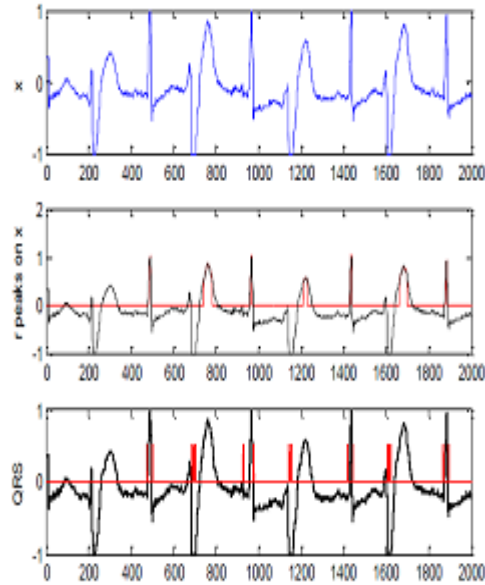
Figure 12. R peak and QRS detection using DOM approach: Red lines denote R peaks and QRS complexes.

The method may not show outstanding efficiency but has its advantages. It is very simple and fast and doesn't involve complex equations as in case of Fourier methods. It is useful in cardiac arrhythmia diagnosis method [14]. Fig. 13 shows R peak detection using continuous wavelet transform.
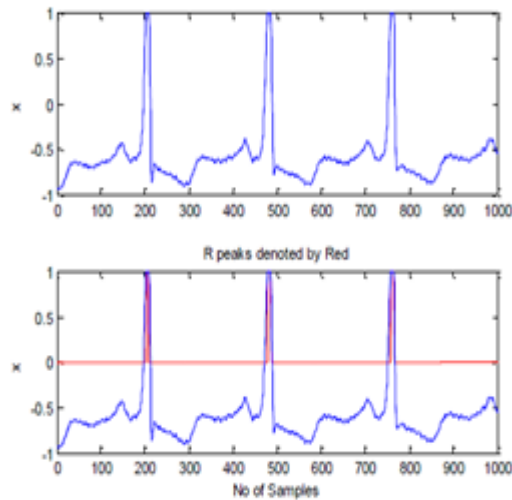
Figure 13.R peak detection using continuous wavelet transform

Table 3: Experimental Results for the use of DOM approach in R peak detection

MIT BIH Record	Actual No of Beats	FP	FN	FP+FN	Detection Error rate = $\frac{FP+FN}{Total\ No\ of\ Beats} \times 100$	Sensitivity Se= $\frac{TP}{TP+FN} \times 100$
200	2601	0	0	0	0	100
201	1963	3	0	3	0.15	100
202	2136	8	0	8	0.37	100
203	2982	6	1	7	0.23	99.9
205	2656	10	0	10	0.38	100
208	2956	8	0	8	0.27	100
209	3004	0	2	2	0.06	99.9
210	2647	10	0	10	0.38	100
212	2748	1	1	2	0.07	99.9
213	3251	7	2	9	0.27	99.9
215	3363	0	10	10	.29	99.7
217	2208	0	0	0	0	100
219	2154	1	0	1	0.05	100
220	2048	2	0	2	0.09	100
221	2427	4	6	10	0.41	99.7
222	2484	6	0	6	0.24	100
223	2605	1	0	1	0.04	100
Average	2448.7	3.9	1.29	5.23	0.21	99.94

Table 4 Experimental results of the R peak detection using CWT

MIT BIH Record	Actual No of Beats	FP	FN	FP+FN	Detection Error rate = $\frac{FP+FN}{Total\ No\ of\ Beats} \times 100$	Sensitivity Se= $\frac{TP}{TP+FN} \times 100$
200	2601	0	1	1	0.04	99.9
201	1963	2	12	14	0.71	99.3
202	2136	8	0	8	0.37	100
203	2982	2	30	32	1.07	98.9
205	2656	0	1	1	0.05	99.9
208	2956	0	5	5	0.16	99.8
209	3004	0	0	0	0	100
210	2647	0	4	4	0.15	99.8
212	2748	0	4	4	0.16	99.8
213	3251	0	2	2	0.06	99.9
215	3363	6	0	6	0.18	100
217	2208	0	0	0	0	100
219	2154	0	0	0	0	100
220	2048	0	0	0	0	100
221	2427	0	4	4	0.16	99.8
222	2484	0	20	20	0.81	99.2
223	2605	0	0	0	0	100
Average	2448.7	1.05	4.88	5.94	0.01	99.84

Table 4 indicates the detection error rates and sensitivity. The detection error rate calculated for this method is 0.01% while the sensitivity is found to be 99.84%. Fig.12 indicates R peak detection using CWT. The CWT method is found to have a good sensitivity. The average detection error rate is very low making this method highly lucrative. Moreover this method is much more evolved than others. The best feature of this method is that it is suitable for non-stationary signals like ECG. Comparing the detection error rates and sensitivity of the different methods in Table 5 we find that CWT is a better choice for R peak detection.

Table 5. Performance comparison of methods of R peak detection

Method	Detection error rate	Sensitivity
Hilbert Transform	0.23	99.8
Difference Operation Method	0.21	99.94
Continuous Wavelet Transform (Proposed Method)	0.01	99.84

6. Conclusion

Sole objective of this project is to develop a method for efficient analysis of ECG signal. In this piece of work, we have proposed a novel method of enhancement of ECG signal using Empirical Mode Decomposition. Deviating from other approaches of using EMD, we proposed the use of low-pass filters for efficient noise removal. A number of earlier proposed methods for R peak detection including Hilbert Transform, Difference Operation Method and Continuous Wavelet Transform were implemented. Efficiency in case of CWT is better as compared to other methods. The average detection error rate for CWT is 0.01% as compared to 0.23% of Hilbert Transform Method and 0.21% of DOM method. The sensitivity of DOM (99.94%) is better than CWT (99.84%), but the low detection error rates compensates for this. Thus the method of signal enhancement and R peak detection using Empirical Mode Decomposition method and Continuous Wavelet Transform is a novel, efficient method having less computation time, hence best suited for analysis of ECG signal for clinical purposes.

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