QRS Detection using EMD and First Order Gaussian Differentiator

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***Abstract*— ECG is a non-invasive technique used as a primary diagnostic tool for cardiovascular diseases. It provides valuable information about the functional aspects of heart and cardiovascular system. In this paper work EMD and FOGD based QRS detection algorithm has been proposed. These methods also find application in speech signal analysis for epoch detection. In speech signal as epoch contains impulse-like function therefore, this method provides zero-crossings at epoch location. Similarly, ECG signal has impulse like function at QRS complex. So, these methods detect only R-peaks very accurately without using any levels of thresholds. Any QRS detection algorithm involves many steps like Filtering and Transformation techniques like Squaring, Averaging, Hilbert Transform, Wavelet Transform and Hilbert Envelope can be eliminated. As, EMD decompose a signal into IMFs. So, task of filtering is accomplished and because first 3 IMFs contain all information about QRS complex therefore, QRS complex can be eliminated from rest of the signal. So, to achieve this signal is reconstructed. This reconstructed signal is fed to negative of FOGD. The FOGD is a first order derivative of Gaussian window. It has anti-symmetric nature so it gives zero-crossing around the peaks. The negative of this FOGD operator is convolved with ECG signal. Search back operation is performed for true peak-detection. The performance of these algorithms was tested on publically available MIT-BIH arrhythmia database. The results obtained are promising and are favorable with existing algorithms.**

Keywords—Electrocardiofram, Emperical mode decomposition, FOGD, IMF.

I. INTRODUCTION

Electrocardiogram (ECG) is a noninvasive technique and is used as a primary diagnostic tool for cardiovascular diseases. The electrocardiogram (ECG) is an important tool for providing information regarding the heart activities. The importance of ECG analysis comes from the fact that it can discover many cardiac diseases. ECG signals are composed of five important waves: P, Q, R, S and T. Sometimes a sixth wave (U) may follow T. Q, R and S is grouped together to form QRS complex. A cleaned ECG signal provides necessary information about the electrophysiology of the heart diseases and changes that may occur. It provides valuable information about the functional aspects of the heart and cardiovascular system [1]. The detection of QRS complex, in particular R peak detection is very important task in ECG signal analysis to extract hidden patterns for monitoring heart rate and arrhythmia detection. Once QRS complex is detected more details can be explored. Much research has been done to develop new algorithms or methods for analysis of ECG signals in these past years.

In recent years many QRS detection algorithms have been proposed based on first order differential and Hilbert Transform based on Hamilton-Tompkins algorithm [2].This is some modified version of Pan-Tompkins algorithm [3].which is based on patient specific threshold. To avoid dependency of subject, Hamilton-Tompkins proposed the rules for finding the thresholds based on root mean square (RMS) value of segmented derivative of the ECG signal [2 ,3]. Search back operation uses second level threshold for detecting the missed beats, especially those which are low in amplitude. But this method does not help in avoiding the misdetection of QRS complex due to presence of noise. Some second order derivative based QRS detection algorithms were also proposed but they did not provide better performance in comparison to that of the first order derivative [4].Besides these, methods based on Hilbert transform were also developed for QRS detection which uses the properties of Hilbert transform [4-5]. One of the important characteristics of Hilbert transform is that as it is an odd function so if there occurs any inflexion point in the waveform it will result in zero crossing. Similarly a, crossing of the zero between consecutive positive and negative inflexion point in them waveform will be represented by a peak in its Hilbert transformed conjugate [6].The first order derivative of ECG signal gives zero crossing at QRS complex. Therefore application of Hilbert transform on this derivative ECG signal provides peaks at the zero crossings. Thus it helps in applying thresholds for QRS complex detection. Using Hilbert transform both first level threshold as well second level threshold based algorithms are developed [4] .Oliveira et.al. introduced Wavelet bases with Hilbert transform for the QRS detection. In this method wavelet bases are used to develop a band pass filter of 5-40 Hz, so that this band contains characteristic frequency of QRS complex. After that the properties of Hilbert transform are applied to detect QRS complex using threshold [7]. C. Li et.al. developed an algorithm based on wavelet transform to detect QRS complex, as well as P and T waves which achieved very significance improvement in detection error rate (DER) [8]. LP residual based algorithms are also developed for QRS detection. A nonlinear transform is applied on the LP residual for distinguishing QRS complex from other waves and noise. Finally threshold is applied to detect QRS complex [9] .Algorithms based on an adaptive matched filter using Artificial Neural Network (ANN) have been developed for QRS complex detection [10].In recent years some Empirical mode decomposition (EMD) based algorithms have also been developed. [11-12].In all above discussed methods, methods based on first order derivative are less complex and easy to implement. Other methods are complex and have used complex transform for QRS detection. Even derivative based method uses multiple levels of threshold for QRS detection. These thresholds are based on some complex heuristic rules. But, when signal to noise ratio is less or low amplitude ECG signal comes, the probability of error occurrence increases, even high artifact in between two R-R interval gives false detection. Thus, the performance of the QRS detection method is limited by the threshold detection procedures and need tuning for new ECG data or set up. What is desirable is a QRS detection method that avoids threshold or uses some simple approach for threshold detection. Therefore for generalization, methods are required that avoid use of such complex procedures for deriving thresholds.

Xing Hongyan et.al. proposed QRS detection algorithm based on EMD. The EMD first decomposed the ECG signal into a series of oscillatory components called intrinsic mode functions (IMFs). Then with soft thresholds de-noising method on the first three IMFs, a detection layer was constructed that was suitable for QRS detection. Using the corresponding relationship between the feature points of the QRS complex and the modulus maxima of detection layer, the QRS complex detection was realized. The proposed EMD method was validated through experiment on the MIT-BIH arrhythmia database and a QRS detection rate of 99.34%was achieved [13] . Weifang Zhu et.al. proposed QRS detection algorithm based on EMD. The EMD methods decomposed the ECG signals into the energy ratio between the first IMFs and the ECG signal was calculated. The ratio resulted to be more than 5%, the detection layer was reconstructed with the first three IMFs which were soft threshold de-noised. Else detection layer was reconstructed with the second third and fourth IMFs. A simple adaptive threshold was then adapted to detect the QRS complex and measures to avoid false detections. The performance when tested using MIT-BIH arrhythmia database achieved average detection rate of 99.62% that shows good reliability of the good detector [14]. According to non-stationary feature of ECG signal, a new classification method of arrhythmia was introduced by Yu-Jing Wang et.al. it combined EMD with singular value decomposition (SVD), using support vector machines (SVM) for classifying. Firstly, ECG signal was decomposed using EMD into a set of IMFs. These IMFs formed the initial feature vector matrix. Then, initial feature vector matrix was decomposed using SVD and singular values of matrix were calculated. These were regarded as the feature vector of ECG signals. Support vector machines used as classifiers were established to identify the condition of arrhythmia. Experimental results proved that this method classified the types of arrhythmia accurately and effectively [15] .Willis J. Tompkins et.al. used EMD for filtering power-line noise in ECG signals. When signal to noise (SNR) is low the power-line noise is separated out as the first IMF. But when SNR is high a part of the signal along with the noise is decomposed as the first IMF. To overcome this problem a pseudo-noise was added at a frequency higher than the highest frequency of the signal to filter out just the power-line noise in the first IMF. The results were compared with traditional IIR-based band stop filtering. This technique was also implemented for filtering power-line noise during enhancement of stress ECG signals [2].

The accuracy and content of information extracted from a recording require an accurate detection of characteristic points from noisy recordings or recordings suffering artifacts and baseline drifts. Therefore, this lead to a possible scope to develop an alternative algorithm to detect QRS complex which can reduce the ambiguity between the R-peaks and noise present in ECG signal. EMD and FOGD are new tools to signal analysis and can be used to develop an alternative algorithm for QRS complex detection.

In literature many algorithms have been developed for QRS detection. Most of the methods are based on thresholds derived by using some complex rules. Such thresholds were only meant for patient-specific ECG data or particularly ECG database. ECG contains 2 types of well-known distortions or noise like base-line drift and high frequency noise like Electromyogram (EMG). Base-line drift occurs during recording of ECG using electrodes and as electrodes are placed on subject's body. So, it also captures EMG signal. So, to filter out these noises from ECG band-pass filters with small bandwidth are required (5-40Hz). The difficulty here arises from the fact that designing such type of filter is a very tedious job. Also, different subjects and even different beats of the same subject have different QRS frequency band and also the frequency bands of QRS and the noise may overlap. So, to prevent this problem alternative QRS detection algorithm need to be developed. In recent years EMD is frequently used as strong signal processing tool and can be used as a replacement of problem of band-pass filter. It also can emphasize the R-peaks which lead to avoid further transformation steps which are used in existing methods. FOGD is used in speech signal analysis to detect epoch locations. Epoch locations are impulse like functions which can be co-related with R-peaks in ECG. So, there is scope to make the detection process more accurate and without the use of thresholds and band pass filter.

II. EMPIRICAL MODE DECOMPOSITION

A new non-linear technique referred to as Empirical Mode Decomposition (EMD), was pioneered by N.E. Huang for adaptively representing non-stationary signals as sums of zero-mean.AM-FM components EMD relies on a fully data-driven mechanism that does not require any priority known basis. It is suited for nonlinear and non-stationary signals, such as biomedical signals. Through a sifting process, the EMD can decompose the signal into a series of intrinsic mode function (IMFs). An IMF is defined as a function with equal number of extrema and zero crossings (or at most differed by one) with its envelopes, as defined by all the local maxima and minima, being symmetric with respect to zero.

Basically IMFs represents the oscillatory modes of a signal. The lower order IMFs represents the fast or high frequency oscillations whereas upper order IMFs correspond to slow or low frequency oscillations. As per the characteristics of ECG, QRS complex is the high frequency component and P and T waves are the low frequency components of the signal. Hence lower order IMFs can be combined together to reconstruct the signal which highlights QRS region over the other waves and low frequency noises like baseline drift due to respiration etc.

EMD can decompose any signal into IMFs .Each IMF contains single frequency at single instant. Therefore, it can be observed that first IMF contains high frequencies at every instant. So, when any signal is decomposed into its IMFs the last IMF is considered as residual IMF. So, if first and last IMF is excluded and signal is reconstructed by using the rest of the IMFs the resulting signal is equal to the signal obtained as the outcome of band pass filter. If most significant IMF containing the maximum information about QRS complex is selected .This means if reconstruction of ECG signal is done by using some selected IMFs containing information about QRS complex it will be very useful for QRS detection which will reduce the ambiguity between real R-peak and artifacts. This EMD based analysis is very useful for r-peak detection. This analysis equals the pre-processing (band-pass filtering) and transformation steps, which are considered as initial steps in QRS detection algorithms.

A. *Empirical Mode Decomposition Description*

The EMD is defined by a process called sifting. It decomposes a given signal x(t) into a set of AM–FM components, called Intrinsic Mode Functions (IMF). Therefore, K modes dk(t) and a residual term r(t)[19] are obtained and expressed by:

$$x(t) = \sum_{k=0}^{K} d_k(t) + r(t), \quad k = 1,2, \ldots . K \qquad (1)$$

The EMD algorithm is summarized by the following steps:

1. Start with the signal dl(t) = x(t), k = 1. Sifting process h (t) = dk(t), j = 0.
2. Identify all local extrema of h (t).
3. Compute the upper (EnvMax) and the lower envelopes (EnvMin) by cubic spline lines interpolation of the maxima and the minima.

$$m(t)=1/M(EnvMin(t)+EnvMax(t)) \qquad (2)$$

4. Calculate the mean of the lower and upper envelopes.
5. Extract the details *h(t) = h (t) - m(t).*
6. If *h(t)* is an IMF, go to step 7, else iterate step 2 to 5 upon the signal *h(t), j=j+1.*
7. Extract the mode $d_k(t) = h(t)$
8. Calculate the residual $r_k(t) = x(t) - d_k(t)$.
9. If r_k (t) has less than 2 minima or 2 extrema, the extraction is finished r(t) = r_k(t) Else iterate the algorithm from step 1 upon the residual r_k(t), k = k + 1.

B. *Empirical Mode Decomposition Steps*

It has been observed that compared to the clean case, most of the components of the first IMF (IMF1) is high frequency noise which may seriously disturb the QRS complex detection. But the amplitude of IMF1 is small, or in other words, the energy of IMF1 is small. In such case, IMF1 is omitted and the second IMF (IMF2), the third IMF (IMF3), and the fourth IMF (IMF4) are used to detect the QRS complex.

Figure 3.1 shows the original ECG (record 219) decomposition using the EMD. IMFs are represented from high to low frequencies.

III. First Order Gaussian Differentiator

In speech signal analysis the first order Gaussian differentiator based method gives zero crossings at the locations of vocal excitation present in signal [17,18]. The first order Gaussian differentiator (FOGD) is a first derivative of Gaussian window. It has anti-symmetric nature so it gives zero crossing at the around the peaks. The ECG has impulse like excitation at the QRS complexes. Considering the properties and application of FOGD operator, a way has been presented to use this operator in QRS detection algorithm. This method does not use any thresholds and has an advantage over reported methods.

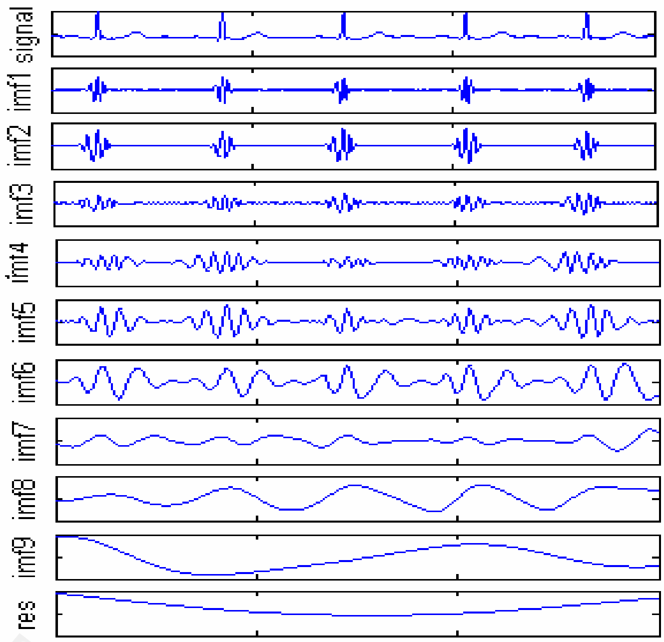

Figure3.1: The original ECG and all the IMFs from first to 9th order obtained after Empirical Modal Decomposition

A. *Basic of FOGD*

First order Gaussian differentiator (FOGD) is the first order derivative of Gaussian window. A Gaussian window of length L is given By:

$$g(n) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-n^2}{2\sigma^2}}; \quad \text{n=1,2,…,L} \qquad ()$$

Where   is the standard deviation. In discrete-time case, the first order Gaussian differentiator is a difference operator given by:

$$gd(n) = g(n) - g(n-1) \text{;n=2,3,…,L} \qquad ()$$

A Gaussian differentiator (see, Figure 2.1) of length L gives the slope at every sample. For 1 n   L/2 the slope is positive, and for L/2+1 n L, the slope is negative.

B. *Properties of FOGD operator*

An impulse sequence which is periodic with N is given by:

$$h(n) = \sum_{k=-\infty}^{\infty} \delta(n - kN) \qquad ()$$

The convolution of h(n) and FOGD is given by:

$$p(n) = \sum_{k=-\infty}^{\infty} g_d(k)\delta(n-k) \qquad ()$$

When the zero crossing of FOGD operator coincides with any impulse, due to the anti-symmetric nature of FOGD operator, the convolution sum will be zero and is accompanied by a positive to negative transition (see, Figure 4.3). This is the basis of this proposed method (see Figure 4.2). The convolution h(n) with negative of FOGD is also giving same output, except the negative to positive transition at the impulse (see Figure 4.3(c)). For convenience, the negative FOGD is used in this study. For example one impulse sequence is given with period N = 50 and convolved output using FOGD of length 200 sample (sampling frequency = 1 KHz) using = 20 are shown in Figure 4.3(b) and convolved output with negative FOGD is shown in Figure 4.3(c).

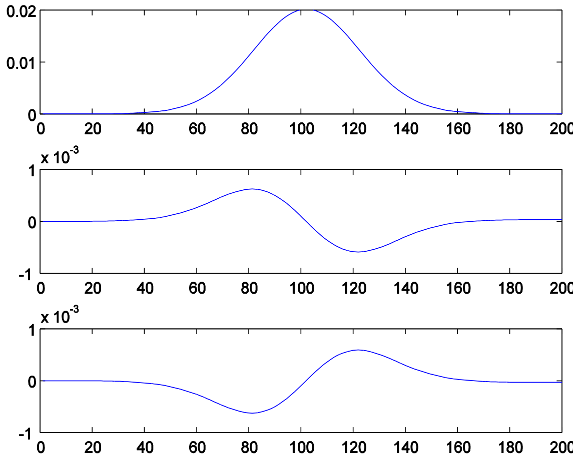

Figure 4.2: (a) Gaussian window of length L=200 with standard deviation 20, (b) First order Gaussian differentiator and (c) Negative First order Gaussian differentiator.

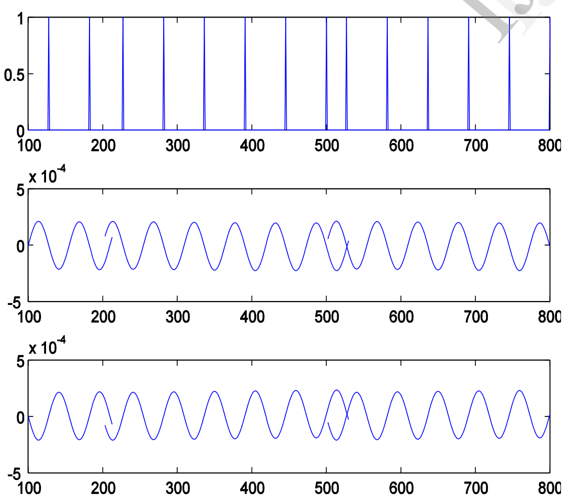

Figure 4.3: (a) A sequence of impulse with period N=50, (b) Output of convolution of First order Gaussian differentiator with impulse sequence and (c) Output of convolution of negative first order Gaussian differentiator with impulse sequence

.QRS Detection using EMD and FOGD

Any QRS detection algorithm involves many steps such as filtering, transformation and peak detection etc. So all algorithm can be categorized in three steps. These steps are:

Preprocessing: In QRS detection first step is band pass filtering to remove baseline drift and high frequency component specially 50 or 60 Hz interference of electric power line. This is more important to separate R peak to other artifacts.

Transformation: To emphasis the QRS complex characteristics from the ECG signal we need transformation. Squaring, Averaging, Hilbert transform, Wavelet transform, Hilbert envelope (HE) is used as a transformation. These transform reduces the ambiguity in false detection and gives a large peak at the QRS complex compare to any other distortion.

Peak detection: Different methods applied on the transformed signal to peak detection. The transformed signal used as a input for different signal processing tools, and applied some decision rules to find real R-peak.

In EMD based algorithms these steps may be merged or can be performed separately. EMD decompose signal in to IMFs. So filtering also can be performed by EMD. Because, first three IMFs contain all information about QRS complex, therefore it is used to eliminate QRS complex So EMD can perform half role of transformation.

The other signal processing method is FOGD which is used for detection of R-peak. Existing methods detect the R-peak based on threshold value. So, threshold plays an important role in R-peak detection therefore the choice of threshold is very critical because it leads to false detections. FOGD overcomes this problem. FOGD is frequently used to locate the pitch instant in speech signal. FOGD is first order differentiation of Gaussian function. It is shown if FOGD convolve with impulse train then, resultant signal gives zero-crossing at the impulse instant. Suppose, if negative FOGD is convolved with impulse train then, negative to positive zero-crossing indicate the impulse instant. Similarly, if positive FOGD is convolved with impulse train positive to negative zero-crossing indicate the impulse instant.

Impulse function represents discontinuity in a signal. By the analysis of ECG signal we conclude that QRS complex is high frequency component of the signal and it creates discontinuities in signal so, it can be considered that QRS complex is like impulse function. This concept is very useful to detect R-peak.

C. *Steps Automatic detection of R-peaks using EMD and FOGD*

1) Decompose an ECG signal into IMFs

2) Reconstruct the signal using IMF2,

3) Convolve the reconstructed ECG signal with negative of FOGD

4) The negative to positive zero-crossings give the location of R-peaks

5) Search-back operation is performed to find the real R-peak over original ECG signal by taking 40 samples backward and forward from zero-crossings.

IV. RESULT AND DISCUSSION

A. *Database for Evaluation*

MIT-BIH Arrhythmia database is used to evaluate the proposed methods for QRS detection and to compare with the existing methods. The database includes 48 ECG recording for different age group of male and female subjects. Each ECG data is of 30 minute long duration and is sampled at 360Hz with 11-bit resolution over a 10mV range.

This database is available on http://www.physionet.org/physiobank/database/mitdb/ with their annotations keys.

B. Evaluation Procedure

The performance of the algorithms are evaluated by calculating the numbers of false positives (FP), false negative (FN) and true positive (TP) for each record. FP is the wrongly detected R peak, FN is the escaped real R peak, and TP is the truly detected R peak. Using these basic parameters, the sensitivity (Se), positive predictivity (+P) and detection error rate (DER) for each method are calculated as,

$$Se = \frac{TP}{TP + FN} \qquad ()$$

$$+P = \frac{TP}{TP + FP} \qquad ()$$

$$DER = \frac{FN + FP}{\# QRS} \qquad ()$$

where #QRS is the no. of total QRS detected.

C. Experimental Details

As discussed above, we carried out our experiments in this section to see the usefulness of the FOGD operator upon some ECG records of MIT- BIH arrhythmia database. The novelty of this method is, it does not use any level of thresholds. The length L of Gaussian window is chosen 450 (samples) with standard deviation = 45, this is equivalent to 10% of its length. It was experimentally observed that this SD is sufficient for the any window length of Gaussian window and giving best result. Again the length of this Gaussian window should be in between the range of 1-2 times of average R-R interval. If window length is too small or too large relative to the average R-R interval then as FOGD spurious zero crossing will come and affects the genuine zero crossing. The negative of this FOGD operator convolved with the ECG signal. The output of convolution clearly shows the rapid changes around the negative to positive zero-crossing. These time instants of negative to positive zero crossings are used as location of R peaks. Due to some noise or abnormal shape of QRS complex, these indexes may be slightly different from the original R peaks. Thus, for accurate detection in this method search back operation has been performed on a ±40 sample window on Hilbert envelope of ECG signal. The location corresponding to maximum points in HE will be giving exact locations of R peak in filtered ECG signal. The reason behind taking 40 samples window is, QRS complex has about duration of 80 - 120 msec. Thus, search operation will be performed in only QRS complex range. These R peaks are compared with the annotation key given for MIT-BIH arrhythmia database.

D. Experimental Results

Proposed method is applied on a segment of ECG signal from MIT-BIH arrhythmia database. Results are shown in figures5.1, 5.2, In Fig5.1 segment of ECG is shown which the original ECG signal is. According to proposed method EMD is applied and ECG signal is decomposed into its IMFs.

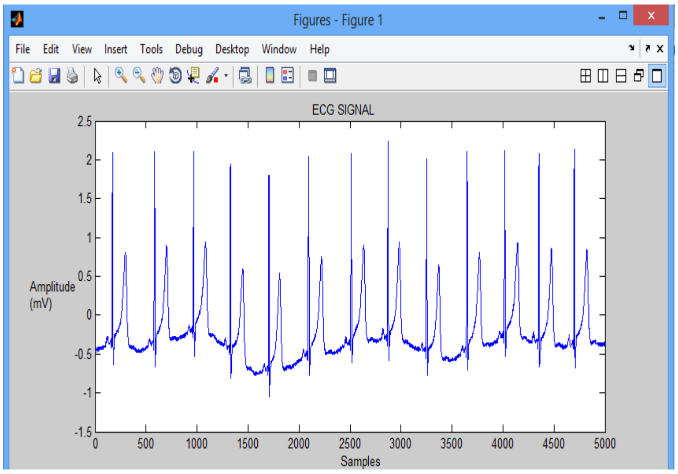

Figure 5.1: Segment of original ECG signal.

Fig5.2 shows the top 6 IMFs of ECG segment. Figure shows the effect of different IMFs. In this figure it can be easily seen IMF1 contain maximum information about R-peaks followed by IMF2 and IMF3. So, in literature different combinations of IMFs are used for QRS detection

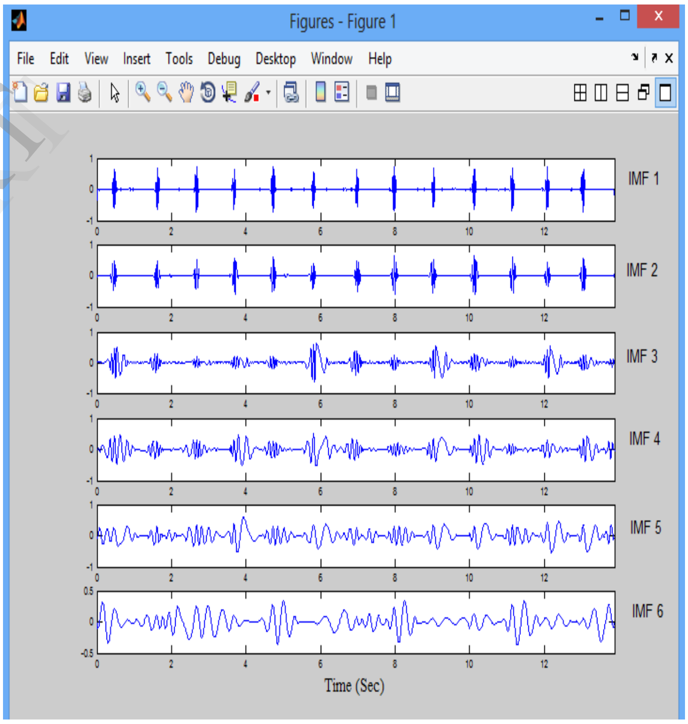

Figure5.2: ECG signal is decomposed into its IMFs by applying EMD.

This method is applied to some records of MIT-BIH arrhythmia database and results are shown in table 5.1

E. Comparison of Performance of Proposed methods with Existing Methods

Comparative study of proposed methods with existing methods is discussed. The description of reference methods is given below: First method is EMD based where EMD first decomposes the ECG signal into IMFs then with soft-threshold de noising method on first 3 IMFs detection layer is constructed and QRS detection is realized using corresponding relationship between the feature points of QRS complex and

TABLE I. RESULTS FROM PROPOSED METHOD

SERIAL NO.	RECORD No.	TOTAL NO. OF QRS DETECTED	FALSE NEGATIVE (FN)	FALSE POSITIVE (FP)	SENSITIVITY (Se)	POSITIVE PREDICTIVITY (+P)	Detection Error Rate DER
1	100	2266	1	1	99.95	99.95	0.08
2	101	1902	3	46	99.83	97.58	2.57
3	103	2078	3	2	99.85	99.90	0.24
4	105	2562	40	36	98.44	98.59	2.96
5	109	2525	6	6	99.76	99.76	0.47
6	112	2532	6	6	99.76	99.76	0.47

TABLE II. COMPARISON OF PROPOSED METHOD WITH EXISTING METHOD

SERIAL NO.	RECORD	Method –I **DER**	Method –II **DER**	**Proposed Method DER**
1	100	0.04	0	**0.08**
2	101	0.27	0.32	**2.57**
3	103	0	0.00	**0.24**
4	105	1.9	2.88	**2.96**
5	109	0.16	0.00	**0.47**
6	112	0.12	0.04	**0.47**

modulus maxima of detection layer. When validated through experiments on MIT-BIH database this method achieved a QRS detection rate.

F. *Discussion*

Performance of proposed method is favorable to existing methods. However DER of proposed method is slightly high than existing methods, but the advantage of proposed method is it does not use any threshold and decision of R- Peaks is made only by zero-crossing points. The other reason for poor-performance is this method is based on windowing process as EMD process is time taking process. So, IMFs are calculated on small segments of ECG signal. In these cases the starting point and ending point occur in between QRS complex. This method is unable to detect R-peak with great precision as in this method first and last R-points are excluded from evaluation.

V. CONCLUSSION

In this work an innovative algorithm for QRS detection technique by using a method combining EMD and FOGD has been developed for QRS detection which is threshold independent and uses a simple procedure for detection of QRS complexes in ECG signal. As ECG signal has impulse like function at QRS complex, so the advantage of this method is that it can detect R-peaks very accurately without using any levels of threshold and the decision of R-Peaks is made only by zero-crossing points. Some selected noisy signals from MIT-BIH arrhythmia database have been tested and it has been observed that the proposed method works well on them as the results are very promising and favorable. It is robust to baseline drifts and to dominant noise.

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