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A Modified Method for ECG Signal Enhancement using EMD based IMF Adaptive Mean Filter

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ABSTRACT

In general, the biomedical signal reflects a combined electrical signal from every organ, indicating a physical variable of importance. This signal may be expressed as a function of time in relation to its amplitude, frequency and phase. Main aim of this analysis work is to generate noise free ECG signals and communicate noise free signals. In our proposed algorithm, both noise removal and peak restoration techniques are used. For this EMD, it is generated Intrinsic Mode Functions (IMFs). EMD splits any signal into a minimal number of intrinsic mode functions (IMFs). Our solution implementation is better than other methods like, DWT, wavelet, wavelet threshold and other techniques. The signal-to-noise ratio (SNR) is used for the efficiency measurement of the proposed system SNR, RMS), and PRD.

Keywords: *Empirical Mode Decomposition (EMD), Intrinsic Mode Functions (IMFs), adaptive Mean and peak restoration*

1. INTRODUCTION

The signal and the unit are the two key variables of signal processing. A signal is a physical quantity with distinct properties of time and space and a system whose input and output is a signal. This study gives the brief introduction about the biomedical signals and the various transformation techniques used for de-noising of the non-stationary signals.

Biomedical signal reflects a combined electrical signal from any organ that represents a physical interest variable. This signal may be expressed as a function of time in relation to its amplitude, frequency and phase. In common, the observations gained from the physiological activities These are recorded to be biomedical signaling, such as gene and protein sequences, heart and neural rhythms, tissue and organ photos. Depending upon their source, application or signal characteristics, the biomedical signals are classified. They can be either continuous or discrete. A number of signal sources may result into a biomedical signal. Those sources are bioelectric Signals, bio impedance signals, bioacoustics signals, bio magnetic signals, biochemical signals and bio-optical signals. Biomedical signal covers a wide range of signals including Electro-Oculogram (EOG) signal, Electroneurogram (ENG) signal, Electrogastrogram (EGG) signal, Phonocardiogram (PCG) signal, Carotid Pulse (CP) signal, Vibromyogram (VMG) signal, Vibroarthogram (VAG) signal, Electrocardiogram (ECG), Electroencephalogram (EEG) and Electromyography (EMG) signal. More precisely, the significant and widely applied biomedical signals are Electrocardiogram (ECG), Electroencephalogram (EEG) and Electromyography (EMG).

A graphic record is the electro-cardiogram or ECG given by an electro cardiographer that registers the heart's electrical activity over time [1]. The signal is obtained through electrical potential calculation between various body sites. ECG indications have a broad range of functions in the medicine area to decide whether the heart operates legally or is abnormal. ECG is the highest cardiovascular arrhythmia assessment standard. It addresses therapy and threat stratification for patients accused of a strong myocardial offence. A retrieval method for electrocardiogram (ECG) operates well when the data are free from disturbances.

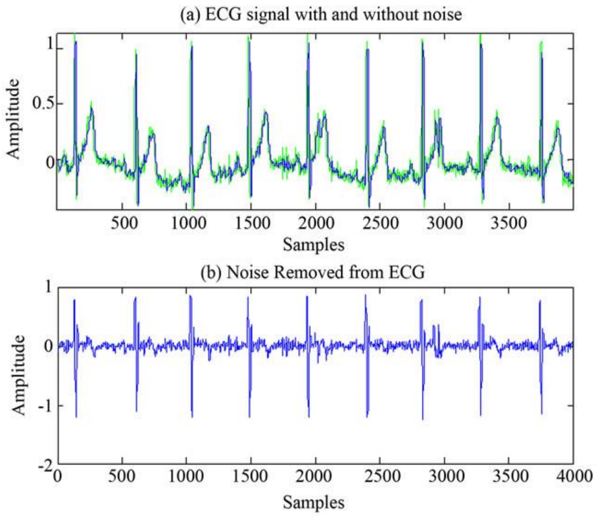

Fig.1: Shows ECG signal de-Noising process

1.1 Empirical Mode Decomposition (EMD)

EMD is a way to disrupt a signal without leaving the time zone. Methods of study such as the transformation of Fourier and the breakdown of wavelets can be contrasted. The method is useful for analyzing natural non-linear or non-stationary signals more frequently.

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This is largely based on the assumptions we've made so far (that the structures involved are, in an estimate or at least, LTI).

EMD feature filters are the full and almost orthogonal basis of the initial signal. The completion of EMD is dependent on completion; it means completeness by the way it is decomposed. Intrinsic mode functions, even if not necessarily orthogonal, are also necessary to define the signals. Every specific data will certainly have data pieces that have the same frequency at different times in the neighboring components. Local two elements, though, should be orthogenic for all practical purposes.

It is therefore possible to retain the various frequencies of time since All functions under which a signal is broken down have the same time-domain length as the original signal. Real world indications must be given to IMFs, as natural processes have many motives, each at certain intervals. This sort of data is apparent in the study of EMD, but is rather hidden in the Fourier domain or in wavelets.

2. PROPOSED METHOD

The complete system model is given in figure 2. The key motivation for the algorithm suggested is to extract ECG signals from the ECG signal. We denoted these IMFs and rebuilt them to obtain an ECG signal for further processing. In this process Reverse Intrinsic Mode Functions (RIMFs) have been generated which is computed by spline function.

2.1 Algorithmic Steps

The first step of the EMD process is to eliminate the interpolation of the minimal range by means of a maximum cubic spline and the lower E-min framework from the signal x(t) originally indicated and the creation of the top covering E max. The total value of the packets is then calculated:

$$m(t) = \frac{Emax + Emin}{2} \qquad (1)$$

The overall value. Eq. 1 is deducted from the initial details:

$$imf_1(t)=x(t)-m(t) \qquad (2)$$

Sifting method is regarded as the above technique.

The input data for the next sifting step is then viewed as imf1(t). The mean value of m(t) in imf1(t), which is omitted from imf1 is estimated and (t). The EMD algorithm is seen as a block schedule in Figure 2.

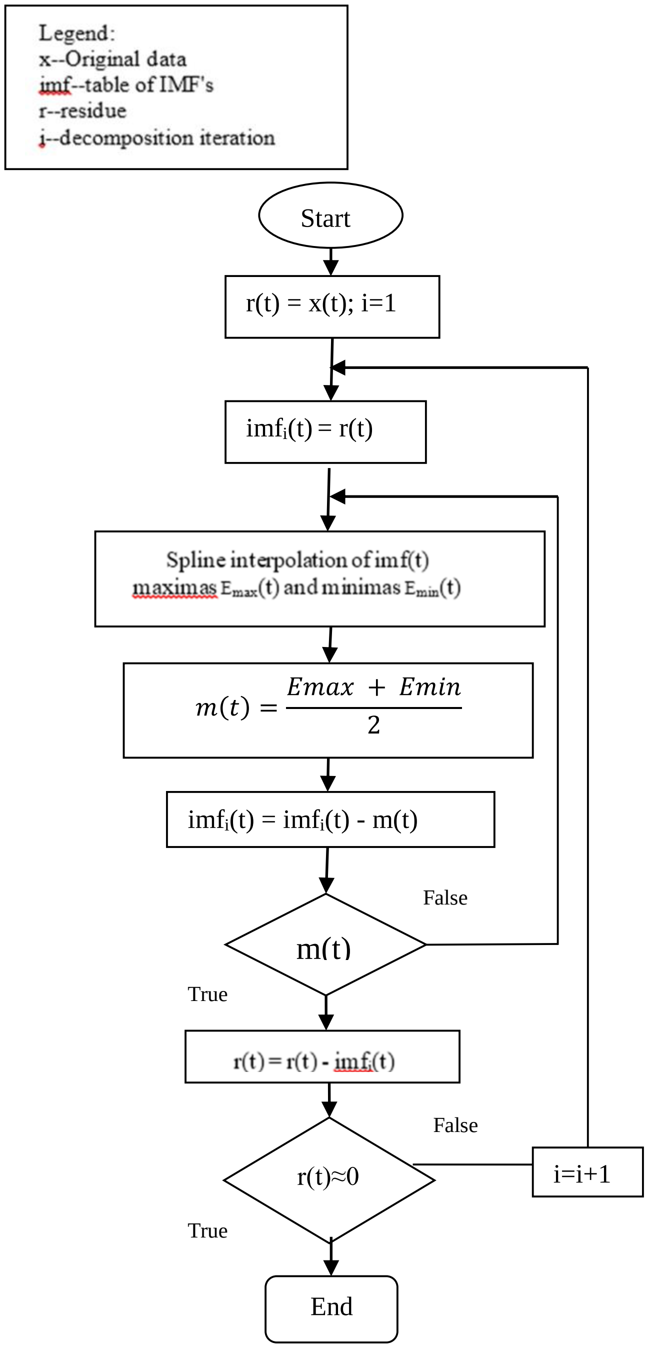

Fig. 2: Flow chart of EMD algorithm

$$imf_1(t) = imf_1(t) - m(t) \qquad (3)$$

The selecting method is repeated until imf1(t) satisfies the requirements of the IMF signal. As the first testing phase stops, the first mode reduces the initial signal. -

$$IMF_1(t):=imf_1(t) \qquad (4)$$

$$r_1(t)=x(t)-IMF(t) \qquad (5)$$

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The subtraction (5) r1(t) residue is stored as data to remove the second IMF (next sifting loop). Both IMFs are removed Procedure:

$$r_i(t)=r_i-1(t)-imf_i(t) \quad (6)$$

If the ri (t) residue reaches three extremes or all points are zero, decomposition is complete. The initial signal is transmitted by all components of the IMF and the rest:

$$r_n + \sum_{i=0}^{n} imf_i(t) = x(t) \quad (7)$$

where n is number of all modes.

After the generation of IMFs these IMFs are added and then
they are compressed and the flowchart for Lempel Ziv compression algorithm is shown, as a flow chart diagram, in figure 2.

2.2 Proposed Modified EMD for ECG signal de-noising

Step 1 – In the first step, pick the ECG signal and then use the signal to pre-process it with the MATLAB protection order. The first task is to turn the image into a normal size using the trigonometric function. After that apply sampling of the signal because the actual ECG signal is too long for the prepressing task and all other items are implemented in MATLAB. A large number of feature files required to execute the initial task in the signal processing procedure.

Step 2 – In the second step apply adaptive white gaussian noise (AWGN) in this ECG signal with the help MATLAB function. Over all process also known as add-noise on the ECG signal and create a noisy ECG signal of different SNR value which is required for result comparison with different methods.
Noisy ECG = AWGN ('input signal', 'SNR in dB')

Step 3 – In this step, apply noise removal in ECG signal. For the first step select the noisy ECG signal then apply EMD process on noisy ECG signal. EMD decompose noisy ECG signals in different IMFs. The process of EMD is already described in the above section 4.3.

Step 4 – Now apply mean filter (MF) of decomposed IMF. Here applies adaptive mean filter. In this process divide a signal into small four elements and apply mean on four values of IMF. Apply same process to all nth IMF.

Step 5 – Now apply IMF reconstruction and create noise free ECG signal.

Step 6 – Apply peak restoration (PR) and calculate the different. parameters of noise free signal for the evolution of noisy ECG signal.

3. SIMULATION RESULT

In this section, we are analyzing projected outcomes of the planned technique. We must use MATLAB R2015b (8.0.0.783) program for simulation of the proposed process. The basic setup of our device is given by the manufacturer: Hewlett-Packard HP 4540s Core(TM) i3-3110M Processor @ 2.40 GHz 2.40 GHz with 4.00 GB RAM: system type: 64-bit operating system.

3.1 Mean Square Error (MSE)

The MSE measures the standard amendment between the actual image (X) and processed image (Y) and is given by:

$$MSE = \frac{1}{N}\sum_{j=0}^{N-1}(X_J - \overline{Y_J})^2 \quad (8)$$

3.2 Root Mean Square Error (RMSE)

The root-mean-square error (RMSE) is a frequently used measure error observation in results. RMSE demonstrates variation between the values predictable by a standard or estimator (sample and population values) and the values currently observed [3].

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=0}^{N-1}(X_J - \overline{Y_J})^2} \quad (9)$$

3.3 Signal to Noise Ratio (SNR)

The SNR contrasts the target signal to the background noise frequency. The greater the percentage of the reverse sound, the less obtrusive. It is seen in decibels (db)

$$SNR = 10\log_{10}\left(\frac{\sigma^2}{\sigma_e^2}\right) \quad (10)$$

Where σ^2 is that the variance of the actual image and σ_e^2 is that the variance of error (Difference between the actual and denoised image i.e. |*X* - *Y*|). Percentage Root-Mean-Square Difference (PRD). The initial signals, x[n] and Åy[n], and their duration N are the signals restored and reconstructed. The PRD is described as:

$$PRD = \sqrt{\frac{\sum_{j=0}^{N-1}(X_J - \overline{Y_J})^2}{\sum_{j=0}^{N-1}(\overline{Y_J})^2}} \times 100 \quad (10)$$

Now shows the original audio signal of input data. We will compress this audio signal by using empirical mode decomposition (EMD) technique to generate different Intrinsic Mode Functions (IMFs).

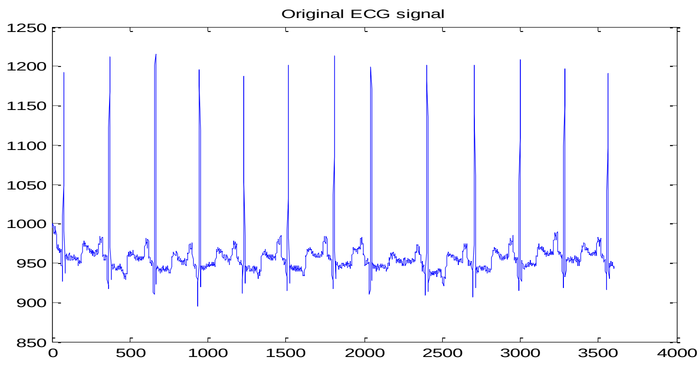

Fig. 3. ECG Signal

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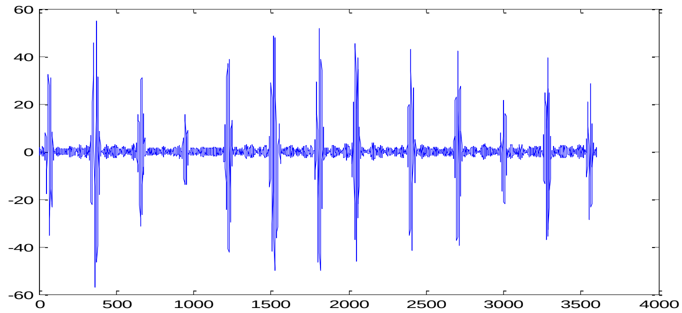

Fig. 4 IMF -1

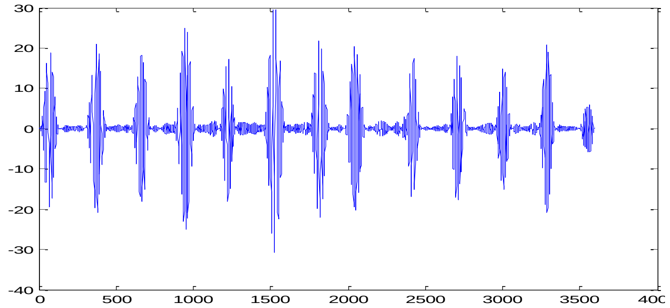

Fig. 5 IMF -4

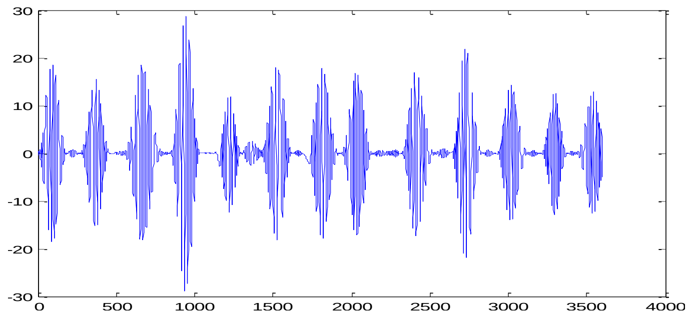

Fig. 6 IMF -5

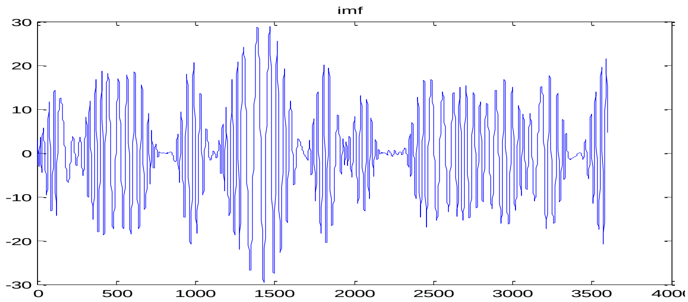

Fig. 7: IMF -6

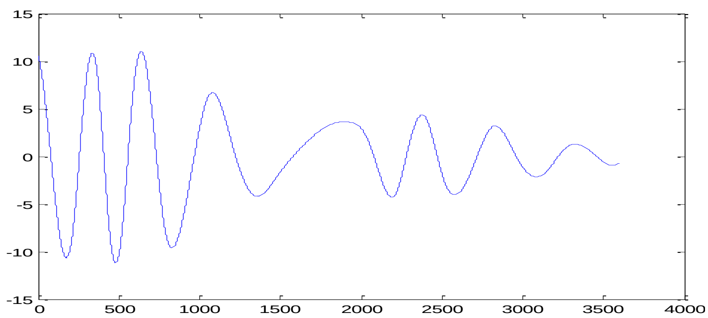

Fig. 8: IMF -7

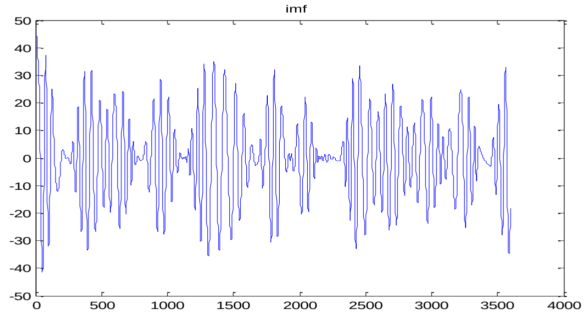

Fig. 9: IMF -8

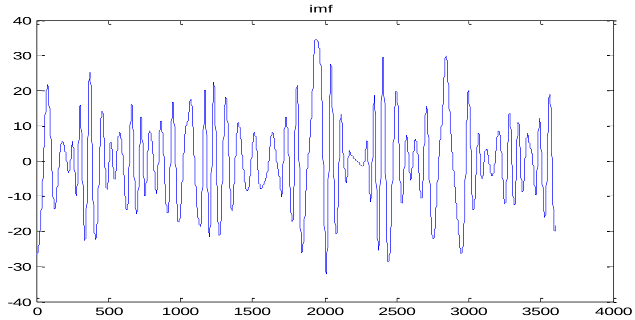

Fig. 10: IMF -9

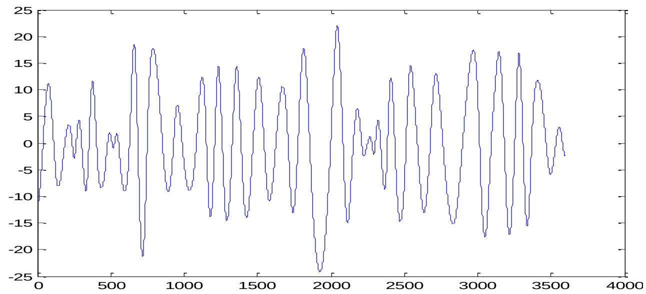

Fig. 11: IMF -10

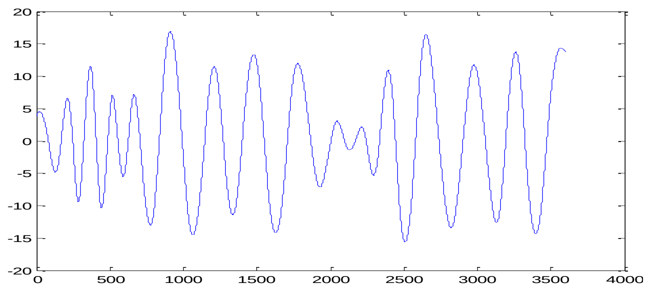

Fig. 12: IMF -11

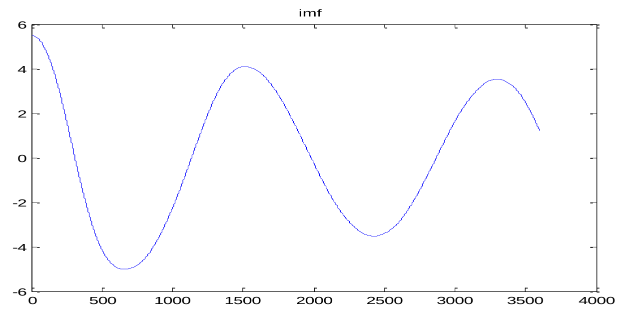

Fig.13: IMF 12

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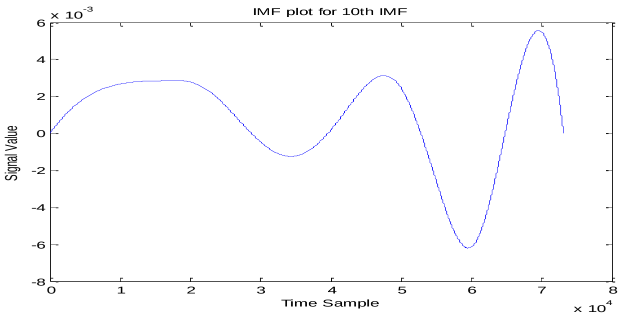

Fig. 14: Shows the IMF-10

From figure 4 to figure 6 we have received various Intrinsic Mode Functions (IMFs) of given input ECG signals. There are different IMF's generated in de-nosing method which are represented as IMF-1, IMF-4, IMF-7, and IMF-10 respectively. From the above diagrams, it clearly shows that the frequency became broader than every slot of signal to signal.

Table 5.1 Shows the RMSE comparison of Proposed Method

Input SNR (db)	Wavelet soft threshold	EMD	EMD wavelet	Base Paper IEEE 2017	Proposed work
6	0.25	0.2	0.17	0.11	0.04
10	0.21	0.16	0.14	0.08	0.03
15	0.14	0.13	0.09	0.04	0.01
20	0.09	0.05	0.04	0.03	0.009

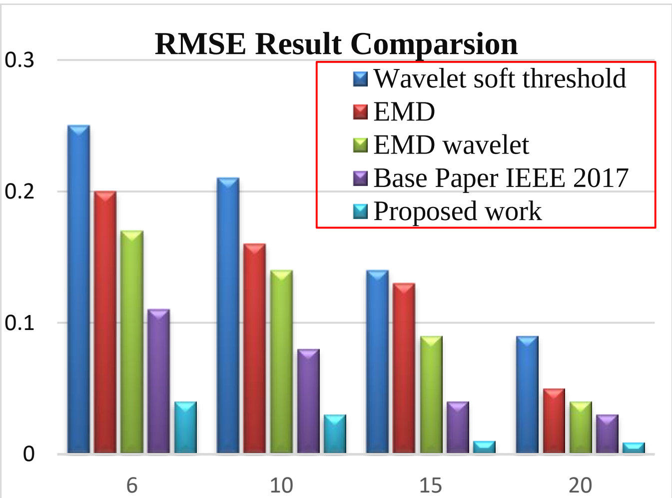

Fig. 15: Graphical analysis of RMSE of Proposed Method

The proposed method is tested on different ECG signals performed with different filters at different SNR values 6, 10, 15 and 20. The above figure shows calculated RMSE (Root mean square Error) on different SNR values. RMSE of proposed de-noising method is least than other different methods. The other methods like Wavelet soft threshold, EMD, EMD wavelet, improved EMD (IEEE 2017) gives lower results as compared to proposed method at different SNR values.

Now move out to the next result of signal to noise ratio (SNR). Compare the resultant output with different previous methods shown in below table 5.2 This table shows the resultant output of proposed method at different SNR values 6, 10,15 and 20db.

Table 5.2 Comparison SNR of Proposed Method

Input SNR (db)	Wavelet soft threshold	EMD	EMD wavelet	Base Paper IEEE 2017	Proposed work
6	5	6.2	8	9.1	8.1
10	5.2	6.1	7	8.9	9.87
15	5.1	5	6.2	8.2	12.43
20	4.1	4.2	5.5	6.7	14.86

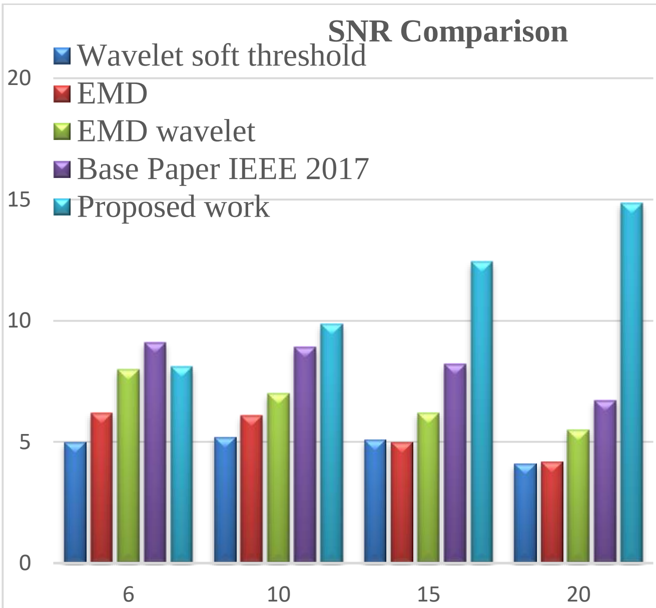

Fig. 16: Graphical analysis of SNR of Proposed Method with different methods

The implemented technique is tested on different ECG signals performed with different filters at different SNR values 6, 10, 15 and 20. The above figure shows calculated SNR on different SNR values. SNR of proposed de-noising method is least than other different methods. The other methods like Wavelet soft threshold, EMD, EMD wavelet, improved EMD (IEEE 2017) give lower results as compared to proposed method at different SNR values.

Now discuss the next result of PRD and compare the resultant output with different previous methods, shown in

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below table 5.3 In this table, the resultant output of proposed methods are different SNR values 6, 10, 15 and 20db.

Table 5.3 Shows the PRD comparison of Proposed Method

Input SNR (db)	Wavelet soft threshold	EMD	EMD wavelet	Base Paper IEEE 2017	Proposed work
6	57	51	48	18	16.15
10	47	43	41	11	10.3
15	32	30	24	6	5.5
20	20	18	12	4	3.2

The implemented technique is tested on different ECG signals performed with different filters at different SNR values 6, 10, 15 and 20. The above figure shows calculated PRD (percentage root mean square error) on different SNR values. PRD of proposed de-noising method is better as compared to other different methods. The other methods like Wavelet soft threshold, EMD, EMD wavelet, improved EMD (IEEE 2017) gives lower results as compared to the proposed method at different SNR values.

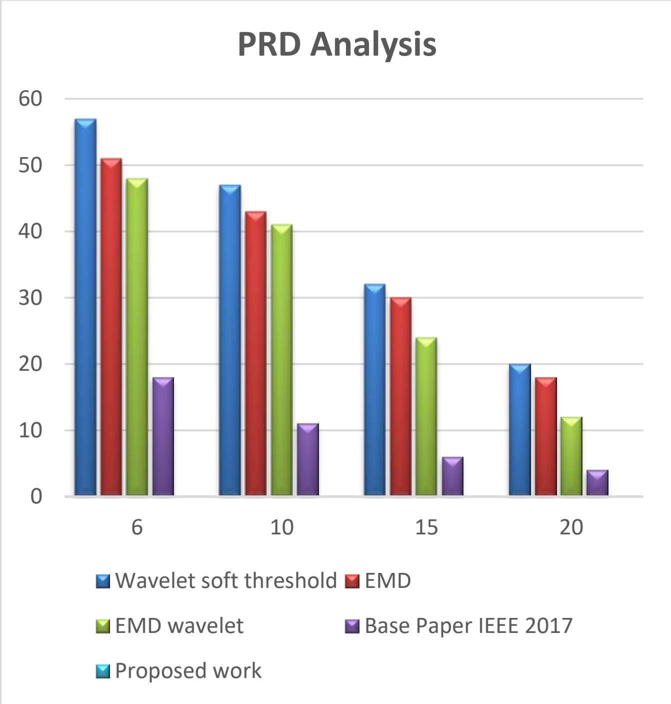

Fig. 17: Graphical analysis of PRD of Proposed Method with different methods

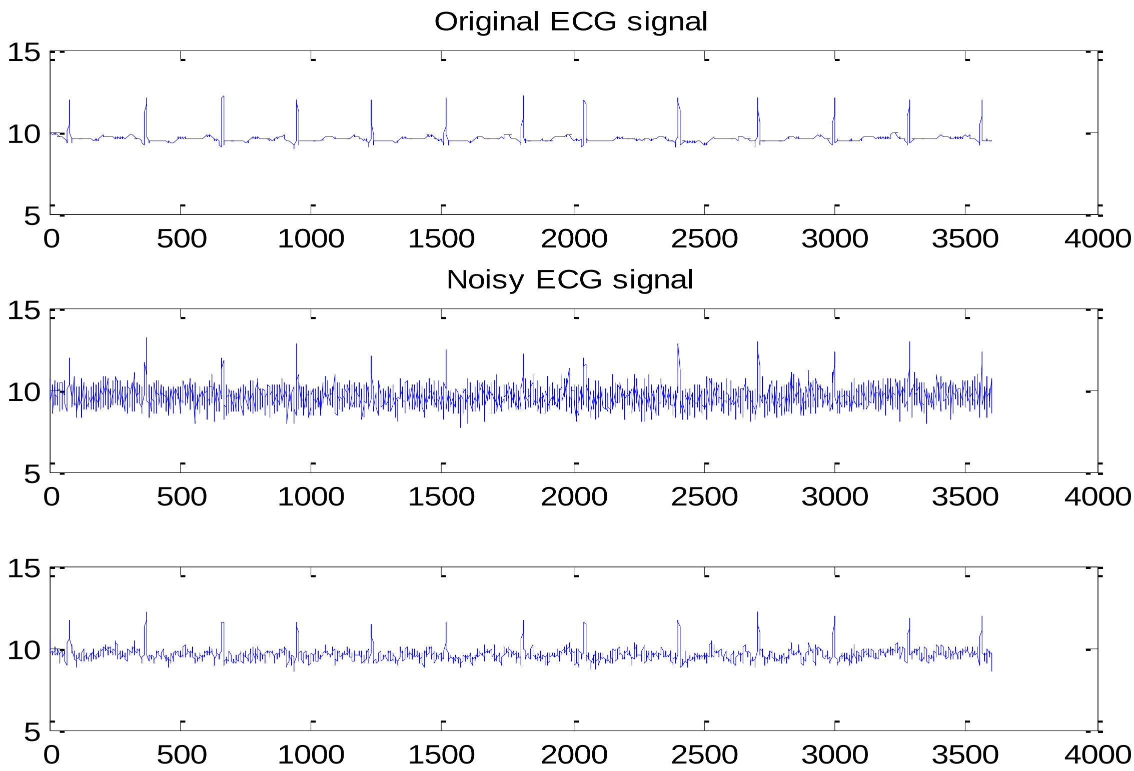

Fig 18: Shows proposed method denoised ECG signal at 6db SNR

4. CONCLUSION

Main objective of this research work is to generate noise free ECG signals. In our proposed algorithm use modified EMD techniques to generate Intrinsic Mode Functions (IMFs) and apply mean filter with adaptive property. The result of Modified EMD shows better result as compared to other methods in terms RMSE, SNR and PRD. Also, calculate two more result parameters which are MAE and MSE both existing in good region. EMD and the adaptive medium filter based on a new system for de-noising ECG signals are the products of the proposed procedure and demonstrate good visual efficiency results. In this initiative, ASMF behavior were used in contrast with traditional EMD-based denoise approaches in which lower orders only represent IMFs in order to improve signal efficiency.

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