



Adaptive ECG Noise Removal Techniques EMD and EEMD

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ABSTRACT: In signal analysis, a lot of efforts are done to improve signal to noise ratio (SNR). Various Filtering techniques (adaptive filtering) are used to improve SNR. The Empirical Mode Decomposition (EMD) and further Ensemble EMD is used for denoising of Electrocardiogram (ECG) signal and Ensemble Empirical Mode Decomposition (EEMD) methods are used to decompose the ECG signal into intrinsic mode functions (IMF). SNR, correlation coefficient (CCR) and Mean Square Error (MSE) are used to measure and compare the performance of proposed methods with traditional EMD based methods. All the experiments done with MATLAB based coding. EMD algorithm performs better than traditional methods. There are the limitations of traditional signal processing tools such as Fourier transform, Wavelet transform as well as Hilbert transform. Empirical Mode Decomposition helps in analysis of signals in time-Frequency domain. The Seismography signals, Bio-medical signals, etc. are those which are nonstationary and nonlinear signal; need to be process on time-frequency basis for better results. So that physical interpretation of underlying dynamic process becomes simple and easy due to time frequency analysis. We have used EEMD for denoising of ECG signal which has resulted in good performance.

KEYWORDS: EMD- Empirical Mode Decomposition; EEMD- Ensemble Empirical Mode Decomposition; IMF- Intrinsic Mode Functions

I. INTRODUCTION

Traditional data analysis methods are used for nonstationary or nonlinear signals. In practical cases, these assumptions failed due to the nonlinear and nonstationary behaviour of signals. We used to analyse the signal's internal fluctuation as a function of frequency, or size scales by using frequency analysis tools. Fourier Transform (FT), Short Time Fourier Transform (STFT), Wavelet transform, Wigner Ville distribution used for time domain signal's time frequency representation [9].

In Fourier analysis, signals which contain multiple frequency components, those signals are described as sum of sine waves, with infinite extent, with different frequencies. Sinusoidal frequency function is independent of time and results only stationary data. That is, the frequency of the signal is independent of time. Also, Fourier analysis global analysis tool because the signal's infinite extent is described by the sine wave. The idea of STFT is to represent a nonstationary signal as a section (block) of stationary signal. Then, for each section we have to calculate the Fourier Transform as well as energy density. Therefore, the original signal can be nonstationary, as long as it satisfies the condition of stationary within each window [9].

However, fixed basis functions is major drawback of Wavelet and it shift out the structures from chosen signal due to its priori basis function. There is chance that the selected mother wavelet may or may not reflect the processes which is actually present in the analyzed signal [8]. Due to wrong selection of wavelets which are used to correlate with signal, may calculate wrong coefficient and variance. This result is misleading and it has no physical meaning.

To overcome these problems, Norden E. Huang proposed Hilbert Huang Transform (HHT) in 1998 [1],[2] which is nonlinear and nonstationary data analysis method. Empirical Mode Decomposition (EMD) is basic building block of HHT which extracts intrinsic mode functions (IMF) from the data itself. As a result EMD is adaptive process which decomposes the signal into fine resolution IMF to coarse resolution IMF. EMD is pre-processing tool for HHT which



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produces better spectrogram as compare to previous Wavelet Transform, Wigner-Ville Distribution , Short Time Fourier Transform (STFT), Fourier Transform, etc.

II. EMPIRICAL MODE DECOMPOSITION

EMD is completely data driven, intuitive, adaptive and locally model free process. Time scales are identified to essence system’s meaningful physical characteristics which further plays a vital role to extract intrinsic mode functions. In EMD, simple natural oscillations mode is the basic building block for any signal. By using simple natural oscillation we can easily reconstruct the original signal. This intrinsic mode of oscillation is modeled by IMF as harmonic’s counterpart. Criteria for IMF are mentioned below:

- 1) The number of local extrema and the number of its zero-crossings must either be equal or differ at most by one.
- 2) At any time t, the mean value of the upper envelope (determined by the local maxima) and the lower envelope (determined by the local minima) is zero.

First condition ensures the traditional requirement of narrow band requirement for stationary Gaussian process. The second condition is new idea to modify the global requirement to local one. Hence, unwanted fluctuations will not affect the instantaneous frequency. For nonlinear and nonstationary signals, ‘local mean’ involves ‘local time scale’ to calculate the mean which is impossible to calculate. As an alternate, we use spline method to define envelopes. These envelopes are defined by local maxima and minima. The IMFs represent the oscillatory modes embedded in signal. Each IMF actually is a zero mean mono-component AM-FM signal with the following form:

$$s(t) = \sum_{j=1}^n a_j(t) \cos \theta_j(t)$$

Where amplitude envelope $a(t)$ and phase $\theta(t)$ are time varying entities [6], [4]. Physical and mathematical meaning is represented by the amplitude and phase. Most signals are not IMFs because they consist of more than one oscillatory mode. In simple words, EMD equivalent to numerical sifting process which empirically differentiate a signal into IMFs which are finite number of hidden fundamental intrinsic oscillatory modes.

Algorithmic Steps:

- 1) Find all local extrema i.e. maxima and minima of signals $s(t)$. Its upper envelope $S_{up}(t)$ and lower envelope $S_{low}(t)$ is obtained by connecting all the maxima and minima of signal $s(t)$ respectively using smooth cubic splines.
- 2) Calculate mean $m_1(t) = \frac{[S_{up}(t) + S_{low}(t)]}{2}$ of these two envelopes from the signal and subtract it from signal to get their difference

$$d_1(t) = x(t) - m_1(t)$$

- 3) Check whether $d_1(t)$ is an IMF. If it is not an IMF, then we should repeat the first and second stage until we get IMF. For that purpose treat $d_1(t)$ as new data and iterate on it and $m_{11}(t)$ is mean for $d_1(t)$

$$d_{11}(t) = d_1(t) - m_{11}(t)$$

- 4) Let us consider after iterating up to n times d_{1n} becomes an IMF i.e.

$$d_{1n}(t) = d_{1(n-1)}(t) - m_{1n}(t)$$

That is designated as

$$c_1(t) = d_{1n}(t)$$

- 5) The first IMF $c_1(t)$ consists the highest frequency component of the signal. The residual signal $r_1(t)$ is given by

$$r_1(t) = s(t) - c_1(t)$$

- 6) Regarding $r_1(t)$ as new data and repeating steps (1), (2), (3) until extracting all the IMFs. The sifting procedure is terminated until the M^{th} residue $r_M(t)$ becomes less than a predetermined small number (0.2 to 0.3) or becomes monotonic. Predetermined small number is given by

$$SD_k = \sum_{t=0}^T \frac{|d_{1(k-1)}(t) - d_{1k}(t)|^2}{d_{1k}^2(t)}$$

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7) The original signal $s(t)$ can thus be expressed as following:

$$s(t) = \sum_{j=1}^n c_j(t) + r_M(t)$$

We have shown ECG signal and corresponding IMFs which are shown in fig. 2 to fig.13 including residue function also [6],[7].

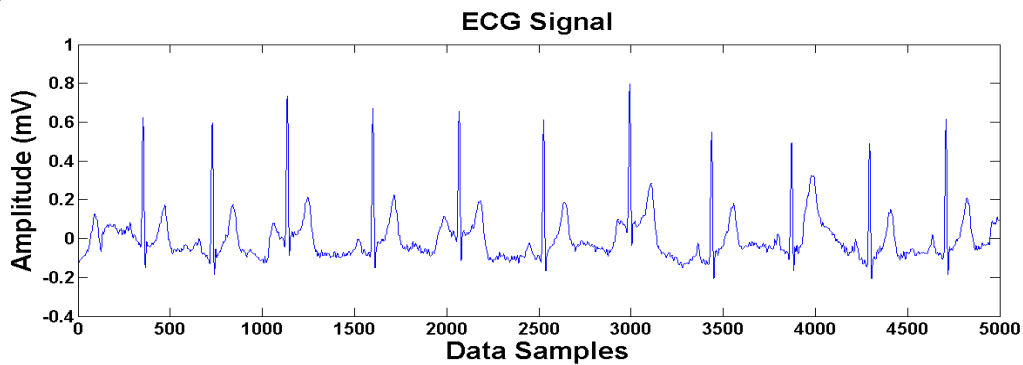


Fig.1 MIT-BIH ECG Database Per1 Rec1 ECG Signal

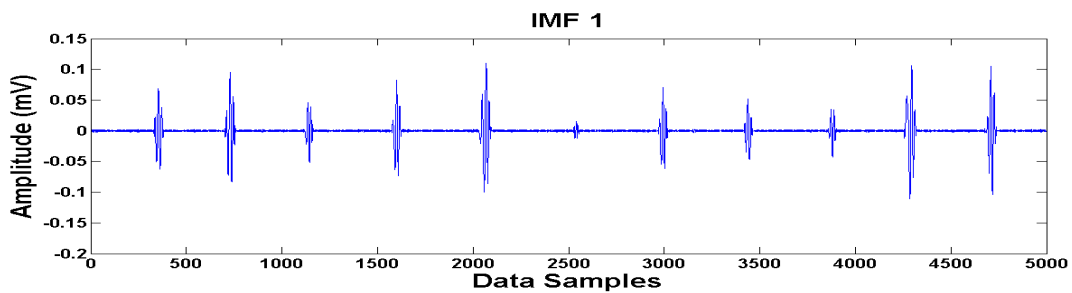


Fig.2 First IMF of ECG Signal

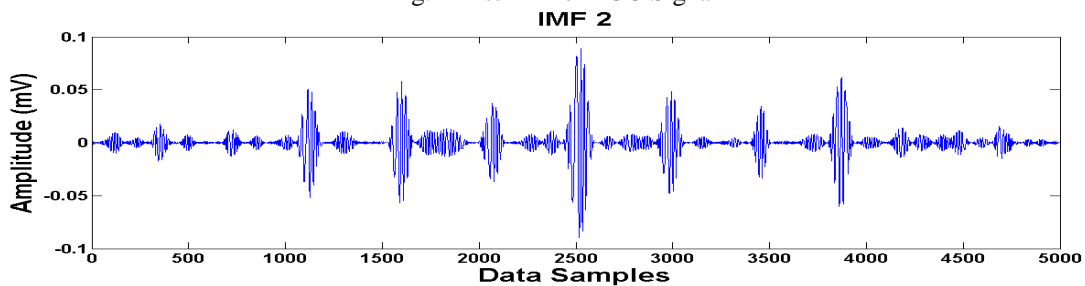


Fig.3 Second IMF of ECG Signal

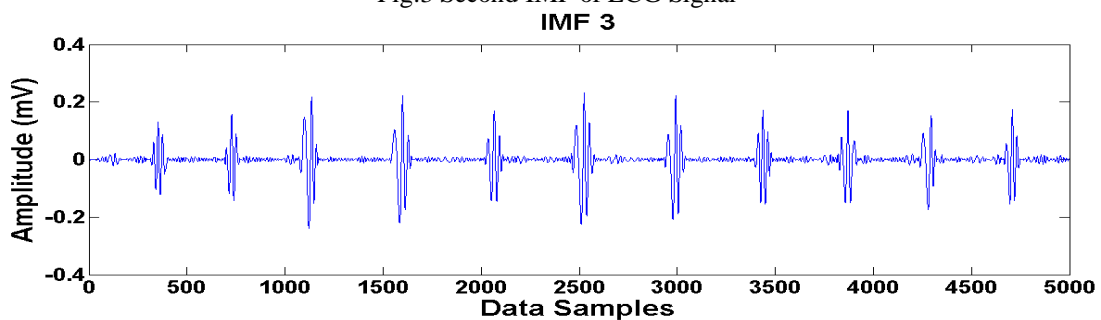


Fig.4 Third IMF of ECG Signal

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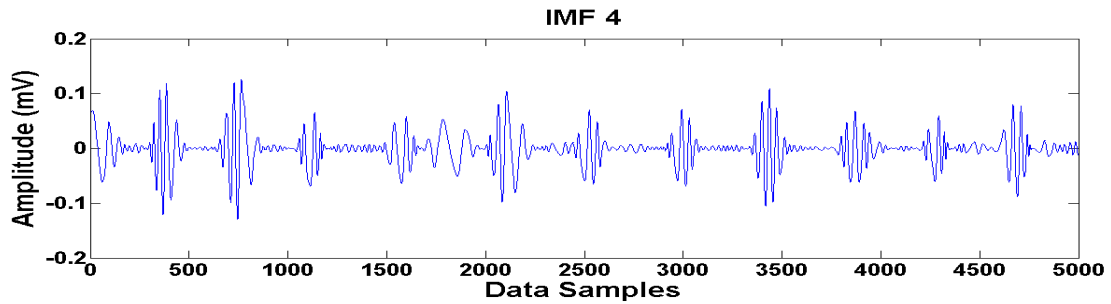


Fig.5 Fourth IMF of ECG Signal

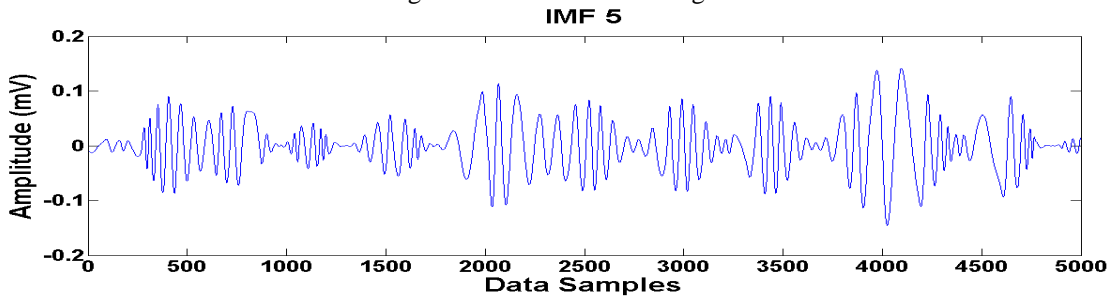


Fig.6 Fifth IMF of ECG Signal

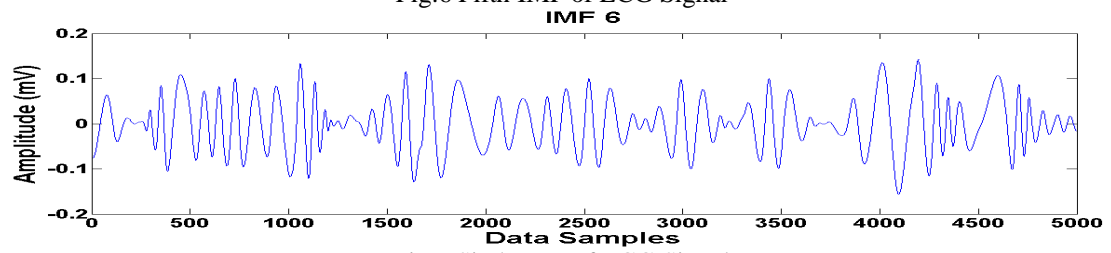


Fig.7 Sixth IMF of ECG Signal

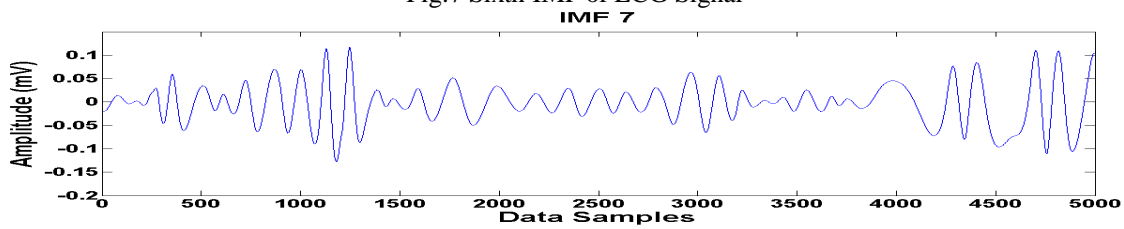


Fig.8 Seventh IMF of ECG Signal

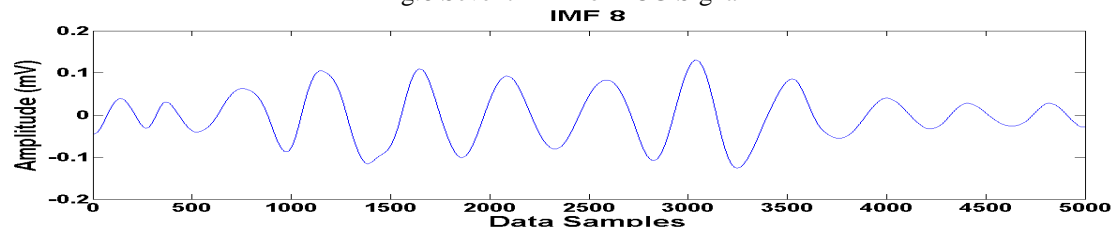


Fig.9 Eighth IMF of ECG Signal

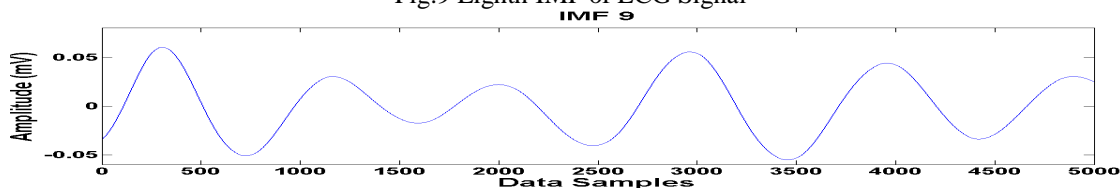


Fig.10 Ninth IMF of ECG Signal

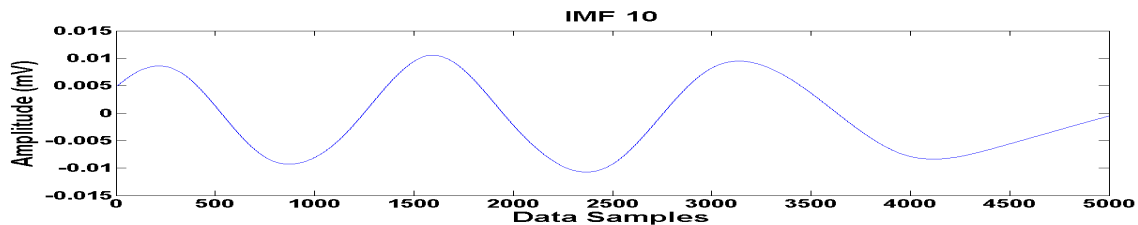


Fig.11 Tenth IMF of ECG Signal

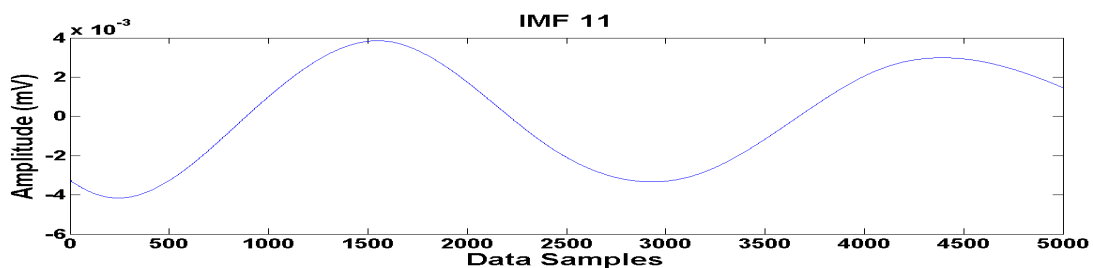


Fig.12 Eleventh IMF of ECG Signal

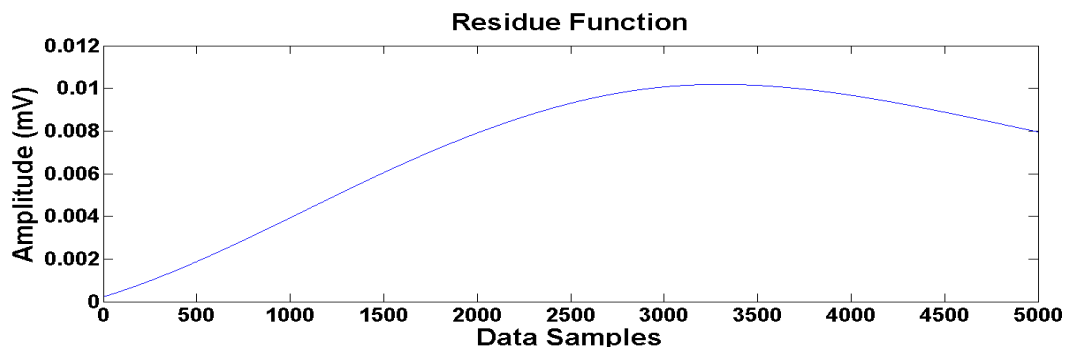


Fig.13 Residue Function

III. ENSEMBLE EMPIRICAL MODE DECOMPOSITION

Mode mixing is very critical point for EMD due to improper characteristics scale. By using white Gaussian noise with signal, EMD behave as dyadic filter bank in frequency domain. But if we try to implement directly EMD, it may lead to wrong result. N.E.Huang [3], [8] proposed intermittence test which is applicable to very specific cases.

The EEMD is based on the following major observations:

1. Only the signal has to survive and persist in presence of noise also. This can be achieved by using adding white Gaussian noise with targeted signal and taking ensemble for 'N' times to cancel it.
2. In ensemble process, the amplitude has to be finite to provide all possible solutions. As a result, the proper IMFs aligned to the corresponding heterogeneous scale signals. These IMFs are dictated by dyadic filter bank to produce more meaningful mean. But, the infinitesimal amplitude may lead to misleading results.
3. Although EMDs physical essence is questionable without noise, EMD is applied to noise added data with large number of trials to obtain proper mean.

An improved EMD algorithm called Ensemble EMD (EEMD) has been developed by which utilizes this characteristic to extract robust and statistically significant IMFs. EEMD is summarized here:

1. Add a white noise series $w(t)$ to the targeted data $x(t)$, the noise must be zero mean and unit variance, so $X(t) = x(t) + w(t)$

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2. Decompose the data with added white noise into Intrinsic Mode Functions(IMFs) and residue r_n described previously.

$$X_i(t) = \sum_{j=1}^n c_j + r_n$$

3. Repeat step 1 and step 2 for N times, but with different white noise series $w_i(t)$ each time, so

$$X_i(t) = \sum_{j=1}^n c_{ij} + r_{in}$$

4. Obtain the ensemble means of corresponding IMFs of the decomposition as the final result. Each IMF is obtained by decomposed the targeted signal.

$$c_j(t) = \frac{1}{N} \sum_{i=1}^N c_{ij}$$

IV. METHODOLOGY

Electrocardiographic device noninvasively records the electrical activity of heart by placing the skin electrodes on designated places. Electrocardiogram (ECG) plays an important role for the diagnosis of heart disease. But the valuable clinical information in ECG is corrupted by power line interference, baseline wander noise, motion artifacts, etc. ECG denoising problem is formulated as, obtaining clean ECG signal from the noisy ECG. The main requirements of ECG denoising methods are:

- I. ECG denoising method should preserve the ECG characteristic waves and it should not disturb the sharp ECG peaks.
- II. ECG denoising should improve Signal to Noise Ratio (SNR).

EMD is used to decompose the ECG into number of IMF components. Lower order IMF components correspond to high frequency and higher order IMF components correspond to low frequency. In general, baseline wander introduce low frequency noise and power line interference introduce high frequency noise. Based on this generalized statement different EMD based ECG denoising methods proposed in literature. In, to denoise the ECG signal, low order and high order IMF components are simply excluded from reconstruction. This is a very simple approach, but in addition to the noise in ECG it also removes the ECG components, because of mode mixing issue in EMD. Mode mixing causes higher order components mixed with lower order IMF components. So simply excluding some of the information containing pure IMF components corrupt the ECG data also. Different approaches both adaptive and non-adaptive techniques were proposed to process the noisy IMF components so that ECG data persevered. In notch filter is used to process the noisy IMF components and then processed IMF components are used for ECG reconstruction. The mode mixing problem is addressed in EMD by adding high frequency noise to the noisy ECG data and then EMD is applied to decompose the ECG into IMF components [4],[5]. Added high frequency noise introduces new IMF components. So identifying the noisy IMF is a trivial task. Here, $x(n)$ is original signal or filtered signal and $\hat{x}(n)$ is reconstructed signal. To evaluate performance of noisy ECG signals, we have used following index parameters signal to noise ratio (SNR), coefficient of correlation (CCR), root meansquare error (RMSE):

$$SNR = \sum_{n=0}^{N-1} \frac{x(n) * x(n)}{[x(n) - \hat{x}(n)]^2}$$

$$CCR = \sum_{n=0}^{N-1} \frac{x(n) * \hat{x}(n)}{\sqrt{\sum_{n=0}^{N-1} x^2(n)} * \sqrt{\sum_{n=0}^{N-1} \hat{x}^2(n)}}$$

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$$RMSE = \sqrt{\sum_{n=0}^{N-1} (x(n) - \hat{x}(n))^2}$$

MIT-BIH ECGID database is used here for the denoising of ECG signal. In database, filter & noisy signals are already present. So with comparison with the filtersignals,we derive the performance index parameter which shows better results.Byusing EMD we get coefficient of correlation as 87% & mean square error as 0.0498 aswell as signal to noise ratio as 14.36 (which are averages of 8 data samples from theECGID database). All these parameters further need to be modified.But by usingonly EMD algorithm we need these results which show better improvement in SNRratio.First we apply the EMD algorithm on ECGID database on person 1 record 1which gives the CCR as 0.8961,MSE as 0.0555 & SNR as 15.The noisy ECG signal &reconstructed ECG signal by EMD is shown below.As EMD is adaptive process & itextracts frequency components from higher order to lower in the form of IMF.So it iseasy to observe those noisy components.As in this example,main noise is presented in the first two or three IMFs.By removing those components,we should get the originalsignal.But due to mode mixing problem,some ECG features also gets removed fromoriginal ECG signal.Still there is need of improvement in results.From the EMD implementation on ECG database, we can conclude that the firstthree IMFs are majorly responsible for powerline noises & residue plus last two IMFsresponsible for baseline noise removal.

Table 1: Denoising of ECG by using EMD

Database (MIT-BIH ECGIDDB)	CCR	MSE	SNR
Per1/Rec1	0.8961	0.0555	15
Per1/Rec2	0.863	0.05	14.3
Per2/ Rec10	0.8709	0.0437	14.6
Per2/Rec22	0.8507	0.0501	13.56
Average	0.87	0.0498	14.36

The principle of EEMD method is that with the statistical characteristics of frequency uniform distribution of white noise,white noise is added to theoriginal signal so that each of the noise-added components consists of the signal andthe white noise, each individual trial may certainly produce very noisy results.Itneeds be noticed that the noise in each enough trails.The ensemble mean is treatedas the true answer because finally,the only persistent part is the signal as more and more trials are added in the ensemble.By using EEMD we get coefficient of correlation as 94.8% & mean square error as0.03 as well as signal to noise ratio as 17.75 (which are averages of 8 datasamples fromthe ECGID database). All these parameters are improved using only EEMD.Theseresults are very good & compare to EMD algorithm results are improved by 8.96%First we apply the EEMD algorithm on ECGID database on person 1 record 1which gives the CCR as 96.02%,MSE as 0.0296 & SNR as 18.The noisy ECG signal& reconstructed ECG signal by EMD is shown below.As EEMD is noise assisteddata analysis method & based on EMD.As a result it gives better results thanEMD.

Database (MIT-BIH ECGIDDB)	CCR	MSE	SNR
Per1/Rec1	0.9602	0.0296	18
Per1/Rec2	0.9474	0.0345	17
Per2/ Rec10	0.9426	0.0282	19
Per2/Rec22	0.9417	0.028	17
Average	0.948	0.03	17.75

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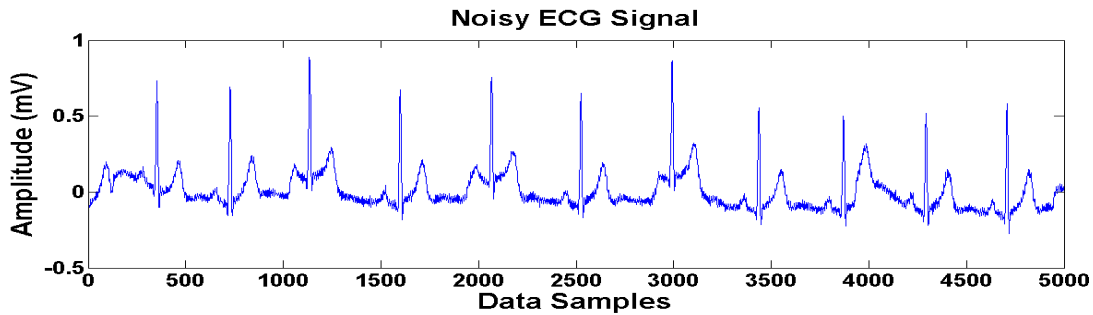


Fig.14ECGID Database Person1Record1 Noisy ECG Signal

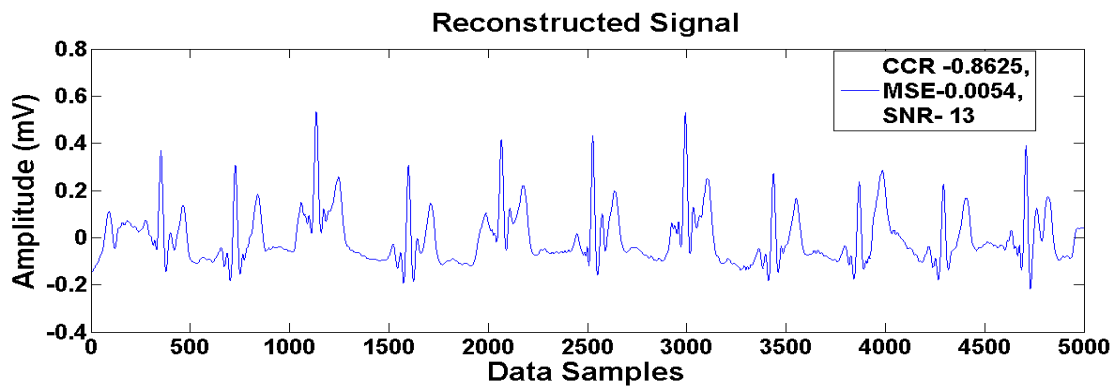


Fig.15ECGID Database Person1Record1EMD recover ECG Signal

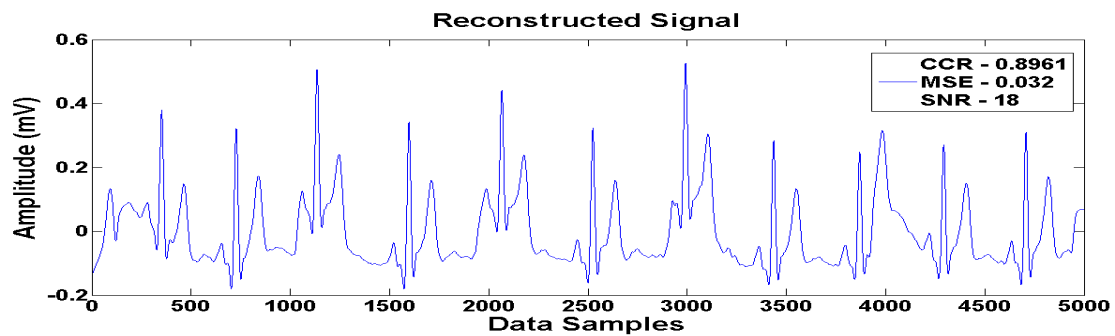


Fig.16ECGID Database Person1Record1EEMD recover ECG Signal

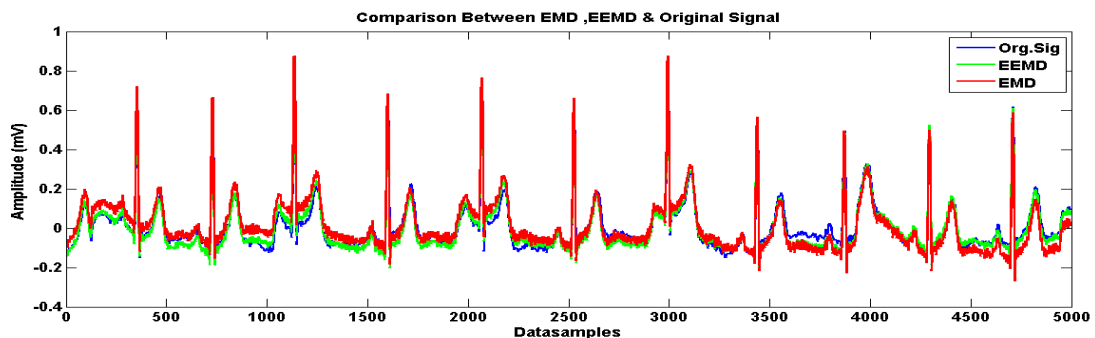


Fig.17ECGID Database Person1Record1 recover ECG Signal comparison

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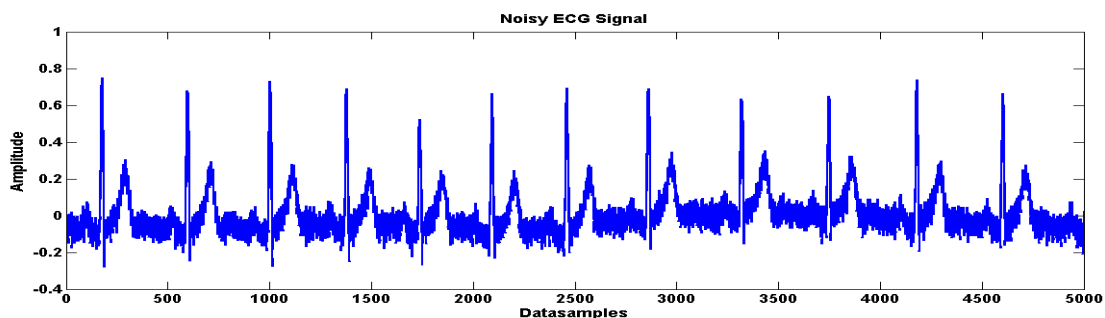


Fig.18 ECGID Database Person1Recorded2 Noisy ECG Signal

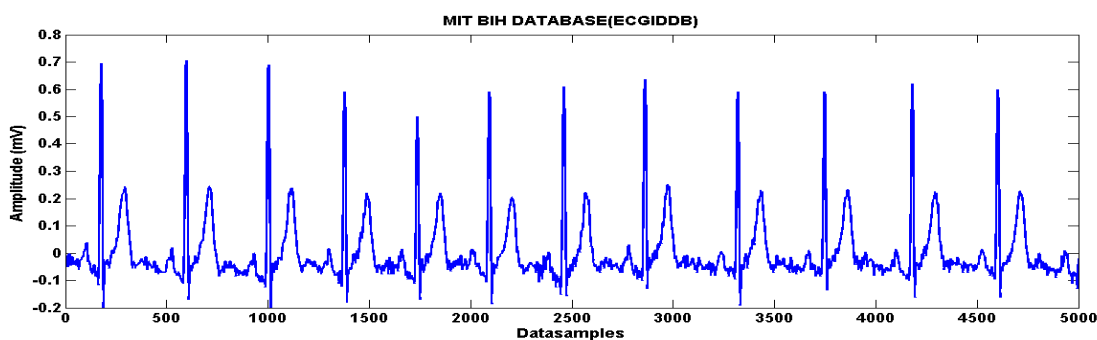


Fig. 19 ECGID Database Person1Recorded2 Filter ECG Signal

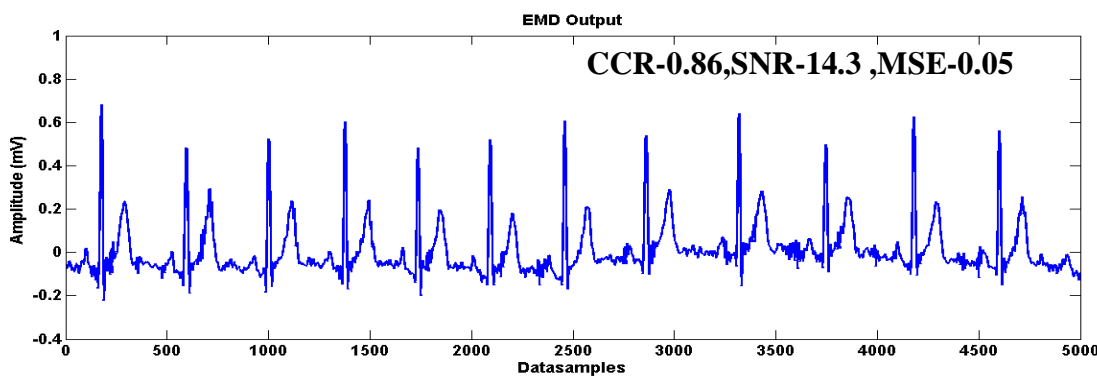


Fig.20 ECGID Database Person1Recorded2 EMD recover ECG Signal

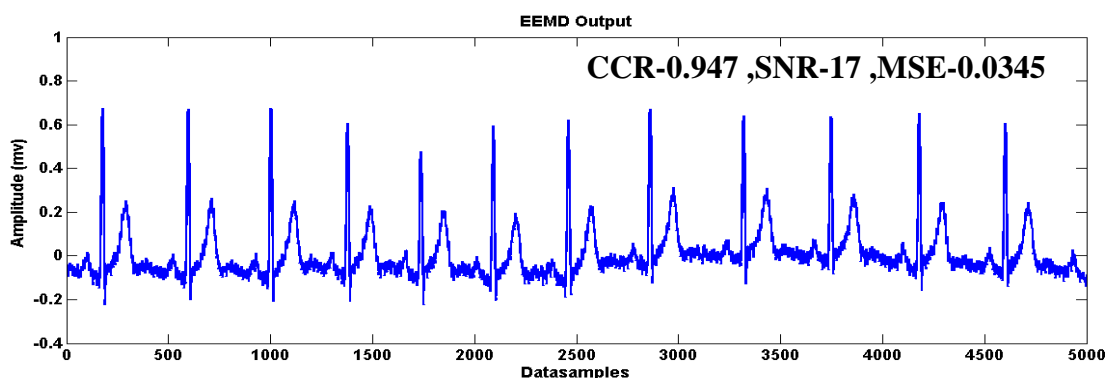


Fig.22 ECGID Database Person1Recorded2 EEMD recover ECG Signal

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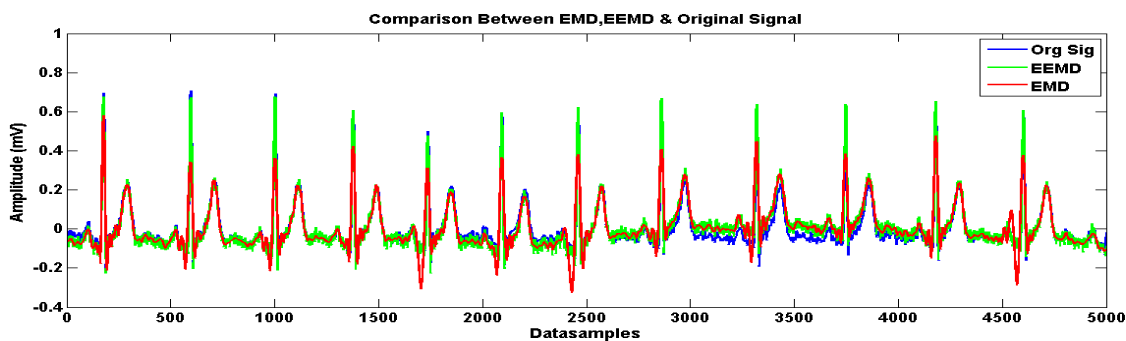


Fig.23 ECGID Database Person1Record2 recover ECG Signal comparison

V. CONCLUSION AND FUTURE WORK

The technique explicated in this work deliberates that on applying empirical mode decomposition to the noisy ECG signal to preserve the useful content of the signal because IMFs include both, the content of the signal as well as noise components. Thus only the actual ECG signal is being considered as the main aim. New algorithms are proposed based on EMD concepts. The performances of these algorithms are demonstrated on real-time ECG data sets from the MIT-BIH database. By using EMD & EEMD, we denoise the ECG signals upto 87%, 94% respectively. In this way EMD & its derivative act as good filter by de-composing the signals into IMFs.

By using EMD and EEMD, we can enhance the features also. EMD extracts the basic oscillatory mode of signals which are best suitable for Hilbert transform. By using Hilbert Huang transform, we can obtain spectrogram. By using suitable Image processing feature extraction tools, we can extract the embedded information from the spectrogram. For example, spectrogram of unhealthy person's ECG should contain the exact information of the disease.

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