QUALITATIVE ANALYSIS OF ECG SIGNAL USING DIFFERENT DENOISING METHODS

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Abstract Abstract: Electrocardiogram **(**ECG) is a versatile tool for detection of cardiovascular diseases. However, during recording of ECG signals, the ECG data gets contaminated by various types of noises like power line interference, base line wander, electrode movement, muscle movement (EMG) etc. Such noises/artifacts mislead the proper diagnosis of heart ailments and hence, their removal is much required. Conventional filters remove the artifacts up to some extent but these filters are static and cannot update their coefficients with change in environment. Hence, adaptive filtering algorithm and Empirical mode decomposition (EMD) are used for artifact removal from ECG signals. Adaptive filters update their coefficients according to the requirement. There are various adaptive algorithms like Least Mean Square (LMS) and Normalized Least Mean Square (NLMS). Inthe present work anAdaptive Algorithmconceptis used for signal denoising. Also,Empirical mode decomposition (EMD) and Ensemble Empirical mode decomposition is used to decompose the signal whose intrinsic mode functions (IMFs) are the mean of an ensemble of trials, each consisting of the signal plus a white noise of finite amplitude.When acomparison of the EMD and adaptive algorithms was made,EEMD method gave better result.

Key Words: EMD, EEMD, IMFs, LMS, NLMS.

INTRODUCTION

The electrocardiogram (ECG) is basically a graphical representation of signals generated by heart beats and its functionality, used for diagnosis of cardiac abnormalities. During ECG acquisition, the ECG signal encountersdifferent types of artifacts like Baseline Wander (BW), Power-line Interference (PLI), muscle movement, electrode movement etc [1]. These artifacts considerably affect the ST segment, diminishes signal frequency resolution, show large amplitude signals in ECG that may resemble PQRST wave forms and hinders proper clinical diagnosisandmonitoring. Overcoming of these artifacts in ECG signals is an important task for better diagnosis. The extraction of high-resolution ECG signals from recordings which are contaminated with background noise is an important issue to investigate. The goal of ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation.

Human heart contains four chambers, the two upper chambers are called the left and right atria, while the lower two chambers are called the left and right ventricles. The atria are attached to the ventricles by fibrous, non-conductive tissue that keeps the ventricles electrically isolated from the atria.The right atrium and the right ventricle together form a pump to circulate the blood to the lungs. Oxygen depleted blood collected through large veins (the superior and inferior vena cava) flows into the right atrium. The right atrium contracts andforces blood to enter right ventricle, stretching the ventricle and maximizing its pumping (contraction) efficiency. The right ventricle then pumps the blood to the lungs where the blood is oxygenated [2]. Similarly, the left atrium and the left ventricle together form a pump to circulate oxygenated blood received through pulmonary veins from the lungs to the rest of the body. Inside the heart a sinoatrial node (SA), a specialized electrical conducting system located below right atrium in the heart sends electrical signals to expand and contract the heart chambers and this SA node is called as pacemaker since it has the ability to initiate electrical pulses at a faster rate of 100p/m. During heart beats, while measuring ECG signal, four waves called as P, Q, R,S and T are recorded as shown in figure 1. The signal generation and its spread is explained below.

P waveshowsthe signal spread from SA node to make the atria contract.P-Q Segment represents howsignal arrives through AV node stay for an instant to allow the ventricle to be filled with blood.Q wave shows how the signal is divided in to two branches after the Buddle of His and run through the septum.R, S wave denotes the contraction of left and right ventricle contraction. T wave representsventricle relaxing [3] [4].

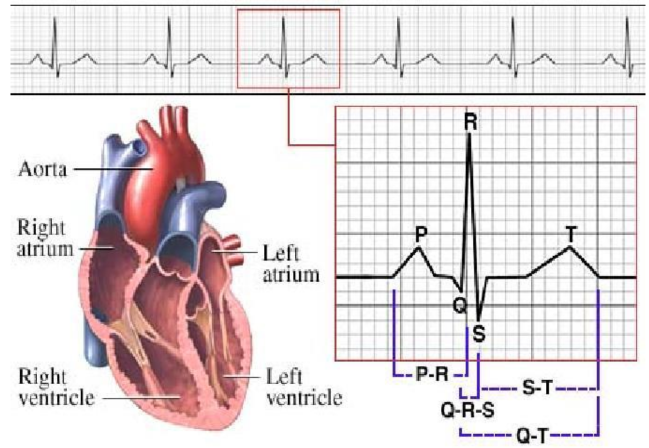


Figure 1: Normal ECG Signal

To over come artifacts encountered during ECG recording, many approaches have been proposed and used. However, each of them has certain limitations, hence biomedical research continues to achieve accuracy in signal quality by effectively denoising the noises. In the present work, adaptive algorithms like Least Mean Square (LMS) and Normalized Least Mean Square (NLMS) were used in addition to Empirical mode decomposition (EMD) and Ensemble Empirical mode decomposition (EEMD) to denoise the ECG signals and their comparative performance is described.

A. EMPIRICAL MODE DECOMPOSITION (EMD)

EMD has proven a quite versatile approach of extracting signal data from noisy non linear and non stationaryprocess .This approach was proposed by Huang et. al [5][6]. The major limitation of EMD is the frequent appearance of mode mixing which is defined as a single Intrinsic mode function either consisting of signals of widely desperate scale which are residing at different IMF components.

EMD adaptively decomposes a multi component signal x(t) into 'L' number of IMFs mathematically it can be represented as

$$x(t) = \sum_{i=1}^{L} h^{(i)}(t) + d(t) \qquad (1)$$

Where *d(t)* is the remainder that is non zero mean slowly varying function with only few extrema [7]. Each of the IMF is estimated with the aid of an iterative process called sifting applied to the residual multi component signal

$$x^{(i)}(t) = \begin{cases} x(t) & i = 1 \\ x(t) - \sum_{j=1}^{i-1} h^{(i)}(t) & i \geq 2 \end{cases} \qquad (2)$$

B. ENSEMBLE EMPIRICAL MODE DECOMPOSITION (EEMD)

To surpass the scale separation problem encountered with EMD without introducing a subjective intermittence test, a new noise assisted data analysis method is proposed called as Ensemble Empirical mode decomposition (EEMD). This approach defines the true IMF components as the mean of an ensemble of trials which comprises signal plus a white noise of finite amplitude. Using this approach it is possible to obviously separate the scale naturally with a prior subjective criterion [8].

To generalize this ensemble idea, noise is introduced to the single data set *x(t)* as if separate observations were indeed being made as an analogue to a physical experiment that could be repeated many times. The added white noise is treated as the possible random noise that would be encountered in the measurement process.

$$x_i(t) = x(t) + w_i(t) \qquad (3)$$

In the case of only one observation, one of the multiple-observation ensembles is mimicked by adding not arbitrary but different copies of white noise $w_i(t)$ to that single observation. Although adding noise may result in smaller signal to-noise ratio, the added white noise provides a uniform reference scale distribution to facilitate EMD.Therefore, the low signal-noise ratio does not affect the decomposition method but actually augments it to avoid the mode mixing [9][10].

Ensemble Empirical Mode Decomposition is developed as follows

1. Add a white noise series to the targeted data;
2. Decompose the data with added white noise into IMFs;
3. Repeat step 1 and step 2 again and again, but with different white noise series each time; and
4. Then, obtain the ensemble means of related IMFs of the decompositions as the final result.

The effects of the decomposition using the EEMD are that the added white noise series nullify each other, and the mean IMFs stays within the natural dyadic filter windows, substantially reducing the chance of mode mixing and preserving the dyadic property [11].

C. ADAPTIVE FILTERING

Adaptive filtering techniques enable to detect time varying potentials and to track the dynamic variations of the signals. It adapts to the change in signal characteristics so as to minimize the error. It is used for adaptive noise cancellation, frequency tracking, system identification and channel equalization. Figure 2shows the general structure of an adaptive filter.

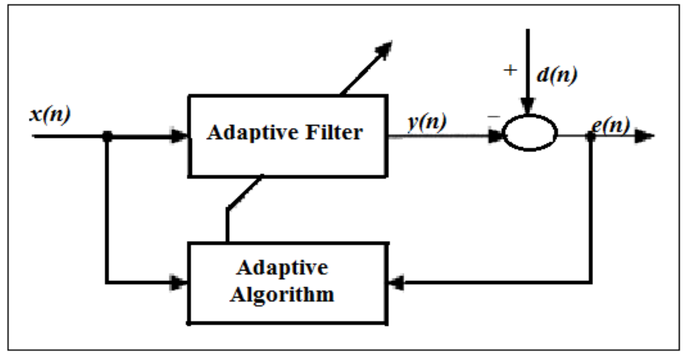


Figure 2: Adaptive Filter Structure[12]

In adaptive filters, the weight vectors are updated by an adaptive algorithm to minimize the cost function. Least mean square (LMS) and Normalized least mean square (NLMS) are important adaptive techniques used here.

III (A) Least Mean Square Algorithm

LMS algorithm is the first widely used adaptive algorithmdeveloped by Bernard Widrow in 1960s [13]. It finds its place in adaptive digital signal processing and adaptive antenna arrays largely due to its simplicity ease of implementation and good convergence properties.LMS Algorithms work as the bench mark to judge all other adaptive filtering algorithms. LMS follows stochastic gradient decent method.In that the filter is only adaptive based on the error at the current time.

LMS algorithm

Initialization

W(0)=0

Algorithm

for=0,1,2,---

$y(n)=w^T(n)x(n)$

$e(n)=d(n)-y(n)$

$W(n+1)=w(n)+\mu x(n)e(n)$

A. Stability of LMS aglorithम :

It can be proved that the LMS algorithm is convergent in mean square only if the convergence rate parameters satisfy

$$0<\mu<2/\lambda_{max} \qquad (4)$$

The correlation λ_{max} is largest given values of matrix of the input signal.But in practical situation, the eigen values of the correlation matrix are not known which makes (4) not much useful one [14]. The useful equation can be derived and given in (5)

$$0<\mu<\frac{2}{\|x(n)\|^2} \qquad (5)$$

The term $\|x(n)\|$ is called as Euclidean norm of the input signal vector. This represents the power of the signal and is usually known or can be estimated a priori.

B. Variants of LMS Algorithm

There are a large number of variants of standard LMS algorithm and each one of them has some advantages and limitations. For instance, echo cancellation requires adaptive algorithm with large memory application and fast convergence but less computational complexity. In another instance like fetal ECG, adaptive filter that may require more number of computations with minimum misadjustments is needed [15]. Among different variants of LMS, NLMS has proved its superiority as the most popular one.

III (B) NORMALIZED LEAST MEAN SQUARE

In standard LMS algorithm, one of the primary disadvantages is having a fixed step size parameter for every iteration [16]. In this, the convergence rate parameters is fixed therefore this can not track the input signal variation properly so an improved algorithm is the NLMS algorithm, where the convergence rate parameter is adaptive. Here optimum value of μ is calculated at every iteration. So that the cost function J(w(n+1)) is minimized at each iteration. However, here μ remains same for entire filter weight vector. Thus μ is a scalar quantity in this algorithm [17]. This algorithm alleviated the problem of gradient noise amplification that exists in standard LMS algorithm and avoid possible instability of the filter. But this requires higher computation complexity. The computational complexity of NLMS algorithm is of 0(N) and requires 3N+3 multiplications.

NLMS algorithm
Initialization
W(0)=0
Algorithm
For n=0,1,2,---
y(n)=WT (n)x(n)
e(n)=d(n)-y(n)

$$\omega(n+1)=\omega(n)+\frac{\alpha}{\|x(n)\|^2+\beta}e(n)x(n) \qquad (6)$$

Simplify a variety of others algorithm may be implemented and their performance may be compared with LMS & NLMS algorithm.

Adaptive filtering techniques enable to detect time varying potentials and to track the dynamic variations of the signals. For instance, least mean square (LMS) based adaptive recurrent filter is used to acquire the impulse response of normal QRS complexes of ECG and then applied it for detection of arrhythmia in ambulatory ECG recordings[18]. The reference inputs to the LMS algorithm are deterministic functions and are denoted by a periodically extended, truncated set of orthonormal basis functions[19]. In such case, the LMS algorithm operates on an instantaneous basis in such a way that the weight vector is updated for every new sample within the occurrence based on an instantaneous gradient estimate.Also several modifications are reported in literature to improve the performance of the LMS algorithm [20]. [21] proposed a noise resilient variable step size LMS which is specially indicated for biomedical applications. Apart from these, other adaptive signal processing techniques like NLMS are reported. In this NLMS algorithm approach, with decreasing stepsize, which converge to the global minimum, a variablestep size NLMS algorithm with faster convergence rate is used.Also several modifications are presented in literature to improve the performance of the LMS algorithm [17, 18, 19, 20]. In time domain, [22]presented severalless computationalcomplex adaptive algorithms. but these algorithms exhibit slower convergence rate. Asmall modification to NLMS algorithm can results a variablestep is inversely proportional to the squared norm of theerror vector. The length of the error vector is theinstantaneousnumber of iterations.

II EXPERIMENTAL RESULTS

To implement and evaluate the current approach it is compared against the multi component decomposition algorithms like EMD, EEMD and Adaptive filtering Algorithms like Least Mean Square, Normalized Least Mean Square. All the experiments were conducted on ECG signals collected from MIT-BIH Data Base. In the figures (3-5) described below, x-axis indicates number of samples and y-axis represents amplitude. Figure 3 shows the original ECG signaltaken from MIT-BIH DataBase and Gaussian noise added to that ECG signal that is Noisy Signal. Figure 4 illustrates intrinsic mode functions from top to bottom where in vertical axis of subplots are not in the same scale..Figure 5 indicates comparision of EMD, EEMD, LMS and NLMS methods. In these four method EEMD method gives better perfomance at 30 dB input SNR. Figure 6 depicts the performance analysis of different approaches using Bar diagram.

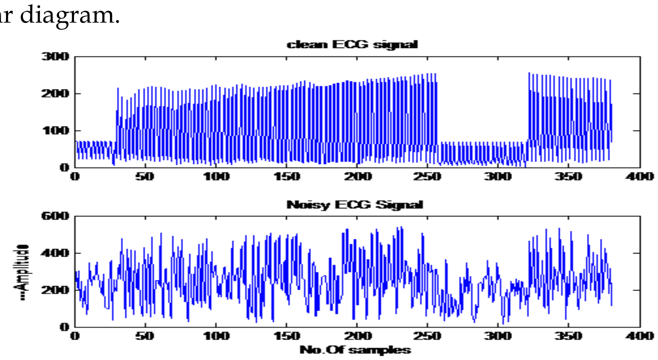


Figure 3: Original ECG signal (200.dat) MIT-BIH&Noisy ECG Signal

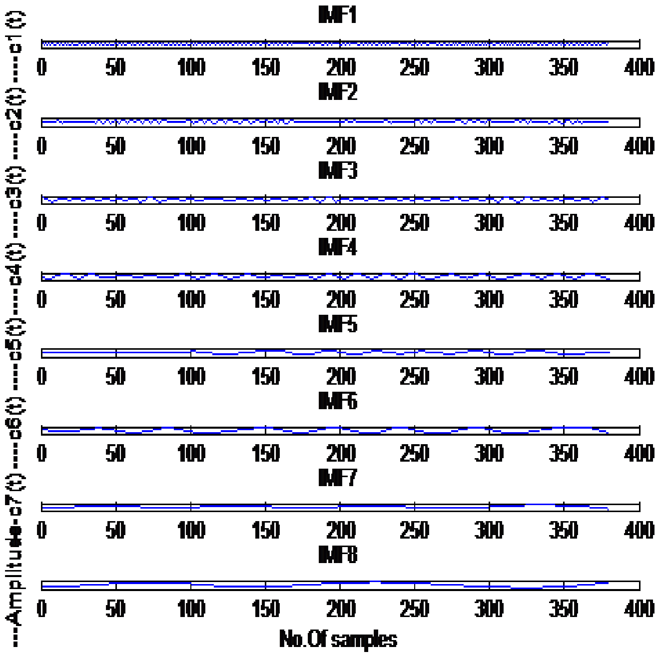
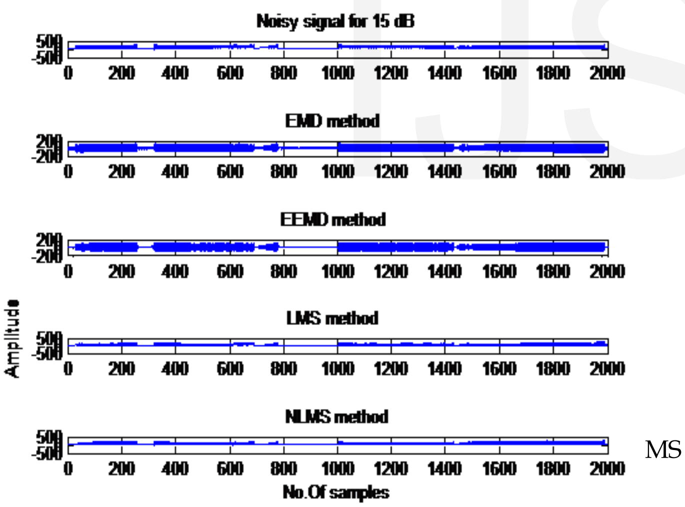


Figure 4: IMF s after EMD decomposition



In table I, 103.data ECG signal from MIT-BIH Data Base at different Input SNRs like 5dB,10dB,15dB,20dB and apply different methods (EMD,EEMD,LMS,NLMS) and get Output SNR values finally the EEMD method gives better performance than other methods.

Table I : SNR values obtained for ECG signal(103.dat) at different input SNRs

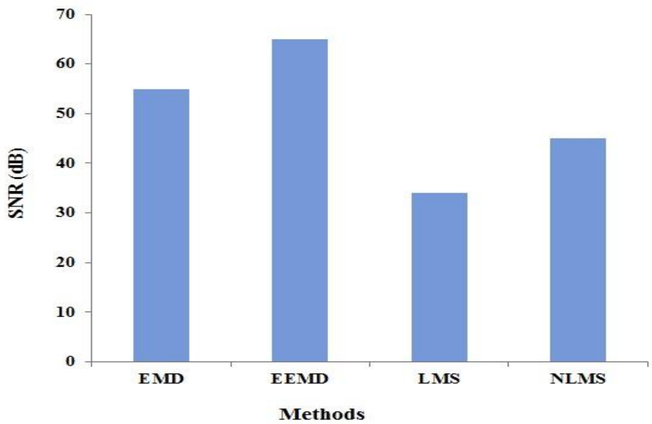
INPUT SNR	EMD	EEMD	LMS	NLMS
5 dB	53.62	55.11	25.36	28.87
10dB	53.67	55.15	25.37	28.92
15dB	53.64	55.13	25.37	28.92
20dB	53.67	55.17	25.37	28.93
AVG	53.65	55.15	25.37	28.92

Table II shows different ECG sinals that were taken from MIT-BIH Data Base and gives fixed Input SNR that is 30 dB and apply different methods finally the EEMD method gives better results than other methods.EEMD approach has substantially improved signal quality than the other methods.

Table II: SNR values obtained for different ECG Signals at Input SNR is 30dB

S. NO	MIT-BIH Data-Base	Adaptive Methods		Decomposition Methods	
	ECG Signals	LMS	NLMS	EMD	EEMD
1	101	24.62	29.63	45.39	51.49
2	103	25.36	28.93	53.64	55.13
3	105	23.46	26.93	56.51	58.70
4	109	25.01	27.63	47.04	47.72
5	111	21.84	27.01	67.63	69.42
6	113	23.63	26.59	52.87	54.86
7	115	24.93	28.96	37.95	40.68
8	118	22.63	24.57	28.40	28.89
9	119	24.23	27.11	44.63	44.87
10	124	23.74	24.78	19.11	19.78
11	200	24.39	27.74	32.87	38.15
12	205	23.12	27.57	73.48	76.07
13	215	24.17	28.11	41.68	42.93
14	230	24.04	28.59	44.99	48.90
15	233	23.11	27.22	62.27	64.88

Figure 6: Performance analysis of different approaches



III.CONCLUSION

In the present study a novel EEMD thresholding approach for denoising ECG signal was proposed. This approach was compared with the EMD denoising approach and Adaptive algorithms like LMS, NLMS. Experimental results were evaluated for the selected ECG signal at different input SNRs at different ECG Signals and different Output SNRs in all the analysis it was found that the EEMD approach has substantially improved signal quality than the other methods. In the analysis it is found that the EEMD approach is leading with another methods of about 20dB-30dB improvement.

Acknowledgment

The authors thank UGC for finantial support

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