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Design of fast and Error free ECG signal filter with LMS Thresholding

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Abstract: An ECG signal is usually corrupted by various types of noises. Some of these noises are power line interface, baseline drift, muscle contraction, motion artifacts, electrosurgical noise, instrumentation noise and electromyography noises. It is highly required to develop a method which can filter ECG signal noises significantly. In this work, an EMD along with adaptive switching mean filter based new method for de-noising of ECG signal has been proposed. Unlike, conventional EMD based de-noising approaches, where only lower orders IMFs are denoised in this work, along with EMD, ASMF operation has been employed for further signal quality improvement. The lower order IMFs are filtered through wavelet de-noising technique to reduce high-frequency artifacts and retain the QRS complexes. Then, considering the effectiveness of ASMF, for further enhancement of signal quality adaptive switching mean filtering is performed. The validity of the performance of the described technique is evaluated on standard MIT-BIH arrhythmia database. Gaussian noise at different signal to noise ratio (SNR) levels are added to the original signals
Keywords: EMD, RMSE, ECG, EMF, PRD

I-INTRODUCTION

The ECG[4] is nothing but the recording of the heart's electrical activity. The deviations in the normal electrical patterns indicate various cardiac disorders. There are various methods to help restore ECG from noisy signal corrupted by various noises. Flow diagram of required work for ECG signal filtering is explained below.

While registering the ECG signal it may get contaminated by random noises uncorrelated with the ECG signal. These noises can be approximated by white Gaussian noise[5]. Thresholding is used in wavelet domain to smooth out or to remove some coefficients of empirical mode decomposition of sub signals of the measured signal. This reduces the noise content of the signal under the non-stationary environment. The proposed method is implemented using following steps.

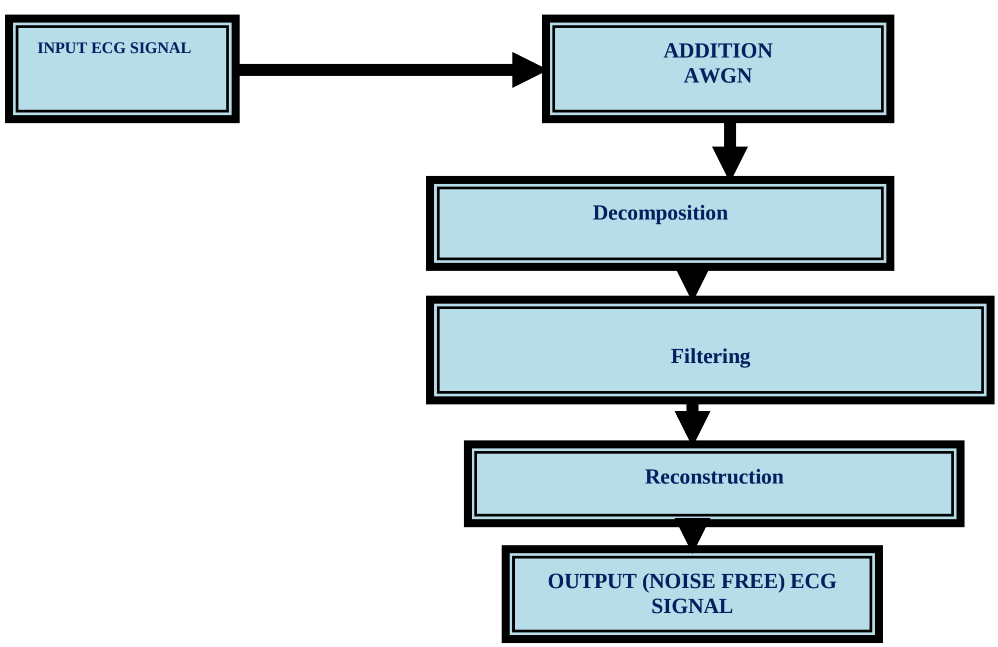

Figure 1 Flow graph of the methodology.

Step 1: ECG signal generation let x(n).
Step2: add random and adaptive white Gaussian noise with different quantity of noise to the ECG signal. White Gaussian noise with zero mean and constant variation is generated and added to the noise free ECG signal. Mathematically this may be written as
y(n) = x(n) + w(n)
Where, x(n) is the noise free ECG signal, w(n) is the white Gaussian noise and y(n) is the noisy ECG signal.
Step 4: Decomposition of the Signal into frequency.
Step 5: choose appropriate filter methid and fiter out the noise from the ECG signal.
Step 6: inverse transform and reconstruct the signal.
Step 7: Signal to Noise Ratio(SNR)[1]-[4] & Root mean square error (RMSE)[1][3] between original signal and estimated signal is computed.
EMD: The Hilbert–Huang transforms (HHT)[1][2][3]. The fundamental part of the HHT is the empirical mode decomposition (EMD)[1]-[5] method. Breaking down signals into various components, EMD can be compared with other analysis methods such as Fourier transform and Wavelet transform. Using the EMD method, any complicated data set can be decomposed into a finite and often small number of components. The EMD method is a necessary step to reduce any given data into a collection of intrinsic mode functions (IMF) [3] to which the Hilbert spectral analysis can be applied.

$$I(n) = \sum_{m=1}^{M} IMF_m(n) + Res_M(n)$$

Where $I(n)$ is the multi-component signal. $IMF_m(n)$ is the M_{th} Intrinsic Mode Function, and $Res_M(n)$ represents residue corresponding to M intrinsic modes.

II-METHODOLOGY

The basic idea behind this thesis is estimation for uncorrupted ECG signal from corrupted or noisy signal, & is also referred to as “signal de-noising”. There are various methods to help restore ECG from noisy signal corrupted by various noises. Selecting appropriate procedure plays a major role in getting desired ECG signal. De-noising methods tend to be problem specific. For example a procedure that is used to de-noise audio signal may not be suitable for de-noising medical signals. Audio signals are stationary in nature whereas ECG signals are non stationary or time varying signals. In this thesis, a study is made on various Thresholding & shrinkage functions are used for de-noising signal & implemented in MATLAB[1]-[15]. Proposed procedure is compared with various Thresholding & shrinkage functions in terms for its SNR & RMSE. For quantify performance for various de-noising algorithms, a simulative ECG is taken & few known noise for example Additive White Gaussian (AWG) is added to it. This would then be given as input to de-noising algorithm, which produces ECG signal close to original ECG signal. Performance for proposed procedure is compared by computing Signal to Noise Ratio (SNR) & Root Mean Square Error (RMSE)[1]-[3].
In case for signal de-noising methods features for degrading system & noises are assumed to be known beforehand. Simulation is carried to produce ECG signal & then Additive White Gaussian noise is added to simulative ECG signal. ECG signal with added AWG noise is given to Empirical Mode Decomposition (EMD) which processes noisy signal & uses filter bank to find its detailed & approximate coefficients for signal. After that Thresholding technique is used. Finally reconstruction for signal carried out. At output expected de-noised ECG signal is obtained. The block diagram shown in Figure 2 is de-noising process. In de-noising for noisy ECG signal[5] EMD is used, signal is transformed. Then Thresholding is used to eliminate noisy components. Finally signal is reconstructed by applying inverse Empirical Mode Decomposition (IEMD)[4].
While registering ECG signal it may get contaminated by random noises uncorrelated with ECG signal. These noises may be approximated by white Gaussian noise. Thresholding is used in wavelet domain to smooth out or to remove few coefficients for wavelet transform for sub signals for measured signal. This reduces noise content for signal under non-stationary environment. Proposed procedure is implemented using following steps.

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Step 1: ECG signal may be develop with help for MATLAB function. Let it is x(n)
Step2: add random & adaptive white Gaussian noise with various quantities for noise to ECG signal. White Gaussian noise with zero mean & constant variation is generated & added to noise free ECG signal. Mathematically this may be written as
y(n)=x(n)+w(n)
Where, x(n) is noise free ECG signal, w(n) is white Gaussian noise & y(n) is noisy ECG signal.
Step 3: apply LMS adaptive filter[9] for filter out unexpected shape from noisy ECG signal. Adaptive filters works on behalf for its available ideal shape for ECG & remove all unexpected shapes.
$z(n)=filt_{LMS}(x(n))$
Step 4: Using an EMD and decompose EMF's[2], to noisy ECG signal is decomposed to obtain approximate & detailed coefficients.
$\{Z_L(\omega), Z_H(\omega)\}=emf\{z(n)\}$
Step 5: Choose a threshold value for Thresholding[13]-[15]. Selection for threshold value plays an important role in de-noising for ECG signal. A number for methods for threshold estimation have been proposed. Thesis work, evaluated performance for following threshold estimators on de-noising for ECG signal.
Universal Thresholding: This is proposed by Donoho. Threshold value[14] T is given by

$$T = \sqrt{2 * log(n)}$$

where, n is number for samples in signal.

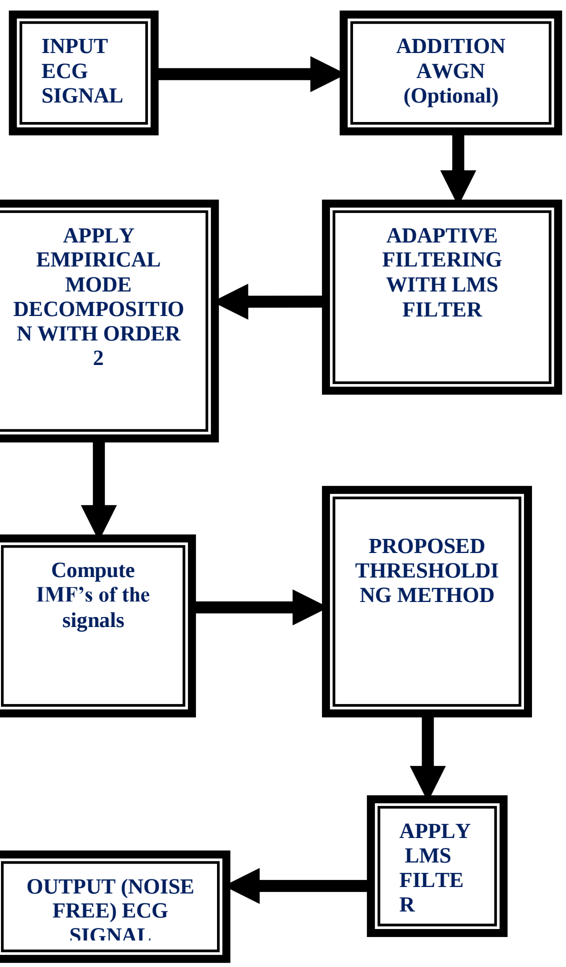

Figure2 Flowgraph for methodology.

Proposed Thresholding method: A new shrinkage function was proposed in this thesis. Parameters for this shrinkage function were optimized by comparing de-noised results for simulative ECG signal at various contaminating levels. For verify de-noised results for represented shrinkage conveniently,) EMD and global Thresholding were used for whole de-noising process. Choice for threshold & shrinkage function is most important step for wavelet de-noising. For obtain best de-noising results, a new shrinkage function which would be used in ECG signals de-noising was proposed here, expressed as formula

$$\hat{Y} = \begin{cases} 0 & |Y| \leq T_L \\ sgn(Y)\left[\dfrac{|Y - T_L|^{\gamma} . T_H}{|T_H - T_L|^{\gamma}}\right] & T_L < |Y| \leq T_H \\ Y & |Y| > T_H \end{cases}$$

Where TH and TL are alterable. This Formula is equal to formula for hard threshold when TL=TH; this formula is equal to formula for firm when γ=1, TL=2/3TH; & same formula is equal to formula for Yasser when γ=3,TL=0.

Step 6: After estimating threshold values, apply Thresholding to shrinkage wavelet detailed coefficient for noisy signal. Normally there are two types for Thresholding methods, hard Thresholding and soft Thresholding[13]-[15]. In hard Thresholding all coefficients below threshold value are set to zero. However in soft Thresholding, in addition to that remaining coefficients are also reduced linearly.

Step 7: After Thresholding compute inverse Empirical Mode Decomposition to estimate original ECG signal.

Step 8: To evaluate performance for proposed method, Signal to Noise Ratio (SNR) & Root mean square error (RMSE)[3] between original signal & estimated signal is computed.

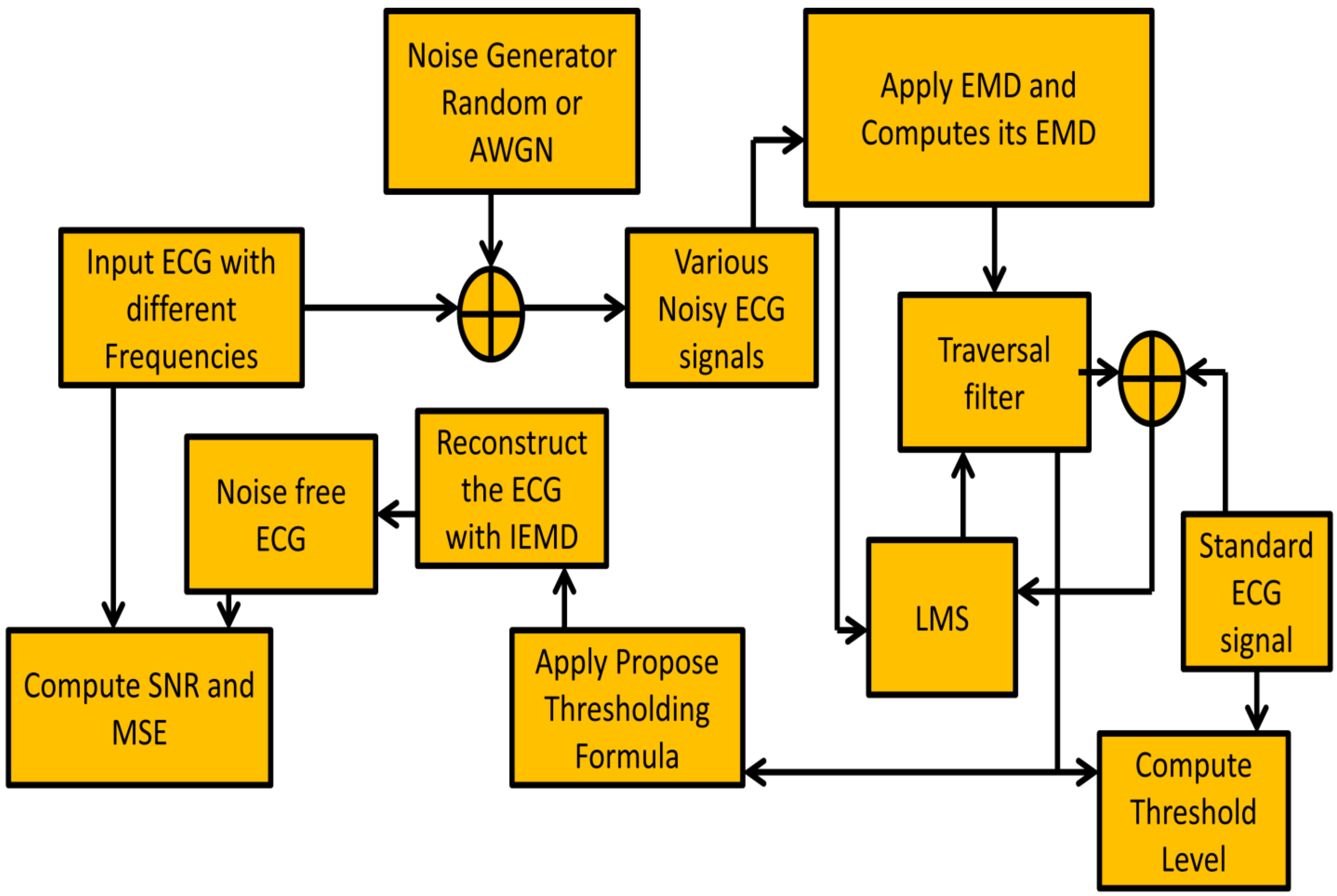

Figure 3 Proposed systems.

Figure 3 above shows block description of proposed procedure as may be observed from block that its proposed design of ECG filtering using two level of filtering first filtering as conventional way of Thresholding where new Thresholding procedure is been proposed & developed, new Thresholding procedure [15] is filtering better than available Thresholding based method, second proposed design is using Least Mean Square (LMS)[9] based adaptive filter procedure which is a iterative adaptive filtering technique which adopt every signal change & filter out all possible noises.

III-RESULTS

Signal to Noise Ratio (SNR): SNR is an important parameter while evaluation or processing for any signal, which gives information about quality for signal. Higher SNR better is performance for system & signal to noise ratio is given by following equation

$$SNR = 10log_{10}\left[\frac{\sum_{i=1}^{N}(filtered\ signal)^2}{\sum_{i=1}^{N}(original\ signal - filtered\ signal)^2}\right]$$

Root Mean Square Error(RMSE): RMSE for original signal & de-noised signal is given by following equation

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{Soriginal} - \mathrm{Sdenoised})^2}$$

PRD: percentage root mean square difference shows the RMSE changes between input and filtered signal.

$$\mathrm{PRD} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{\sum_{i=1}^{N}(x_i)^2}}\ \mathrm{X}100$$

MIT-BIH arrhythmia database: The MIT-BIH Arrhythmia Database[1]-[3] contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database. Figure 4 is graphical user interface for user interface where use can perform followings:- Provide input signal Noise ECG signal input is taken through MIT-BIH Arrhythmia Database[1]-[3] Three isolated graphs shows the original ECG, Noisy ECG and filtered ECG The GUI also shows the output results of RMSE, PRD[2], PSNR, Cross correlation and Absolute MSE[1]

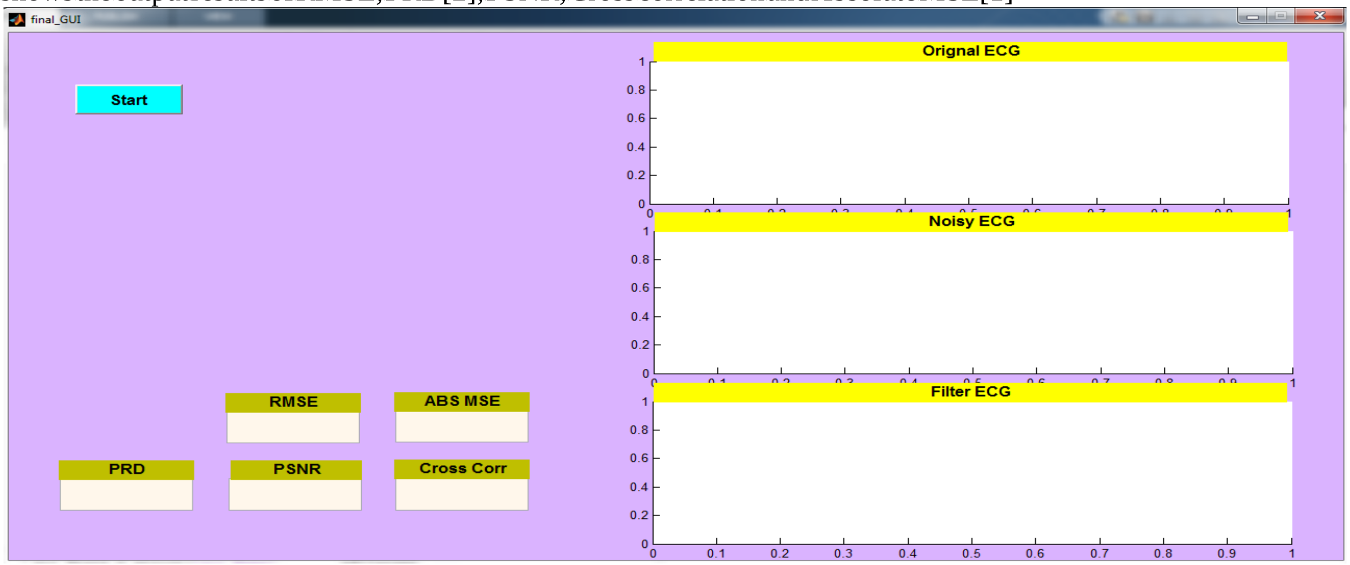

Figure 4 GUI developed for user interface.

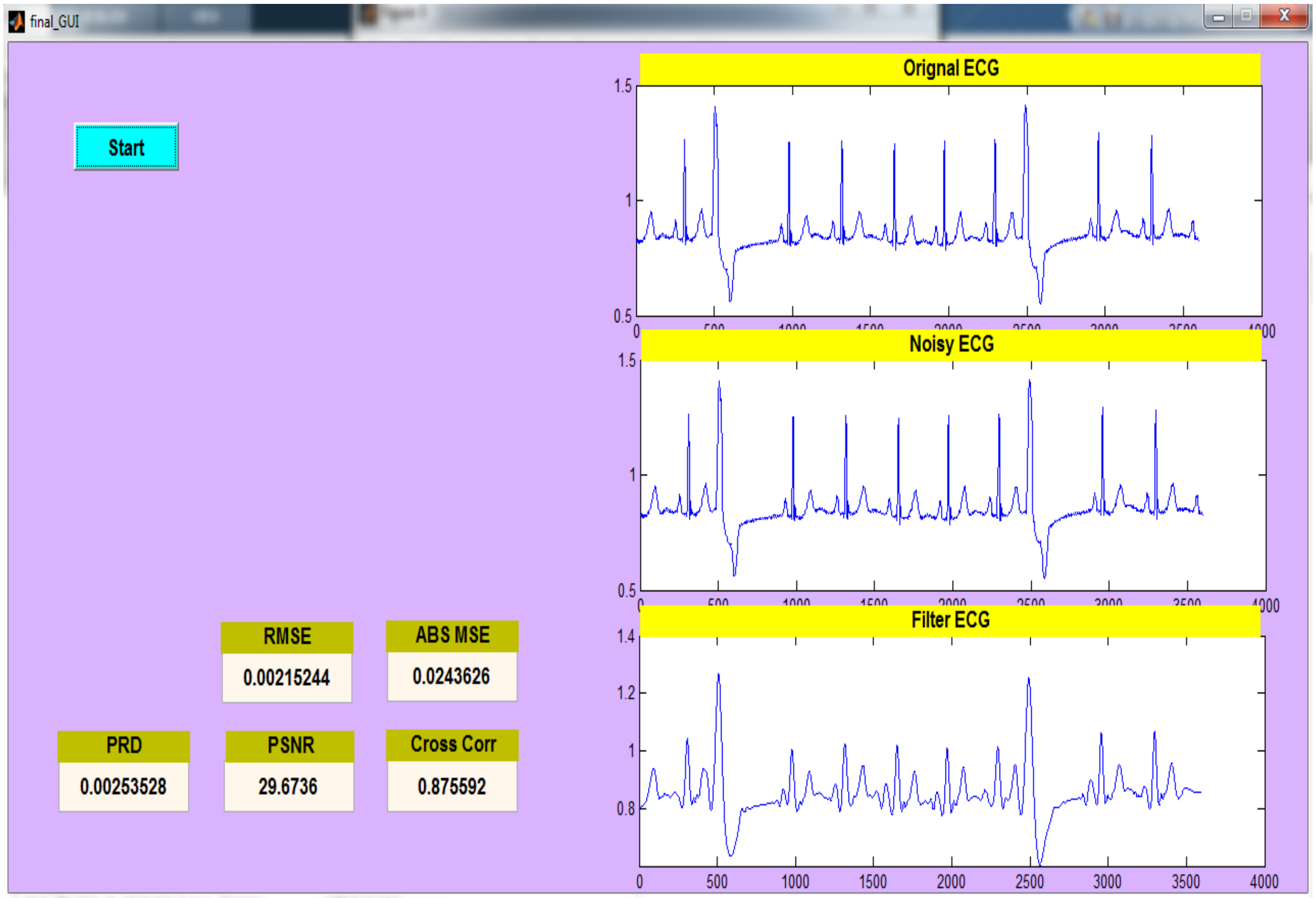

Figure 5 Observe results for the MIT-BIH database 100.

ECG data from standard MIT-BIH arrhythmia database have been utilized for performance evaluation. Simulation Results observe for the The ECG signals, namely 100m, 101m, 103m, 105m, 115m and 215m are employed. These ECG records contain normal, abnormal ECG beats and time-varying QRS morphologies
Table 1 blow shows the results of PSNR and RMSE observe for the different MIT-BIH database (100, 101, 103, 105, 115, 215) ECG signals. Table also shows the results obtain by Manas Rakshit work and ECG filtering with EMD only and make comparison with all. The observe results are without adding any external noise in the MIT-BIH database signals.

MIT-BIH database	**PSNR**		
	Proposed	Manas Rakshit	EMD only
100	32.3424	18.8345	16.8006
101	30.0379	18.5727	15.1525
103	24.7261	17.3609	14.7374
105	47.2972	23.5749	23.6749
115	30.1308	20.1399	16.7369
215	38.5656	24.4461	19.3686

Table 1 PSNR comparison without external noise in MIT-BIH database.

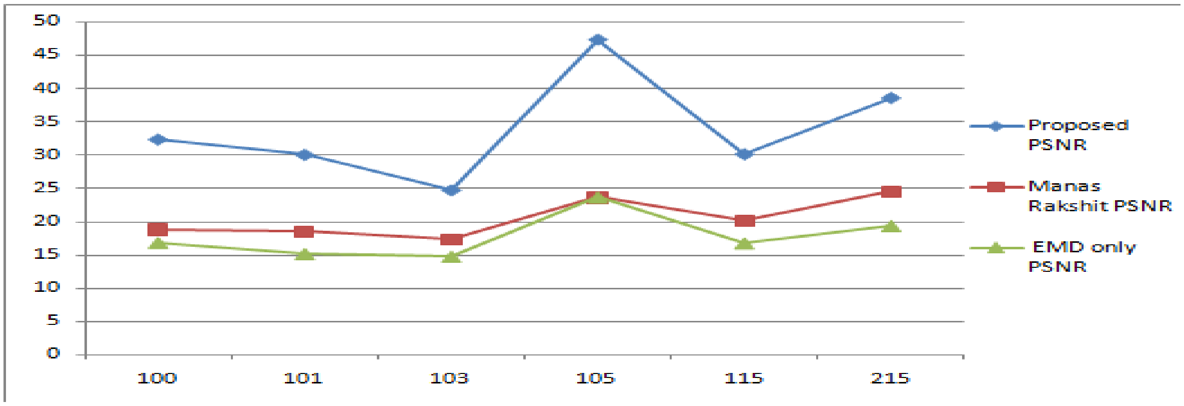

Figure 6 PSNR comparison without external noise in MIT-BIH database.

MIT-BIH database	RMSE		
	Proposed	Manas Rakshit	EMD only
100	0.001164	0.004479	0.0034
101	0.001224	0.003031	0.004161
103	0.007843	0.008691	0.009325
105	1.96E-05	0.000459	0.000104
115	0.002009	0.00296	0.00362
215	0.000244	0.000566	0.00103

Table 2 RMSE comparison without external noise in MIT-BIH database.

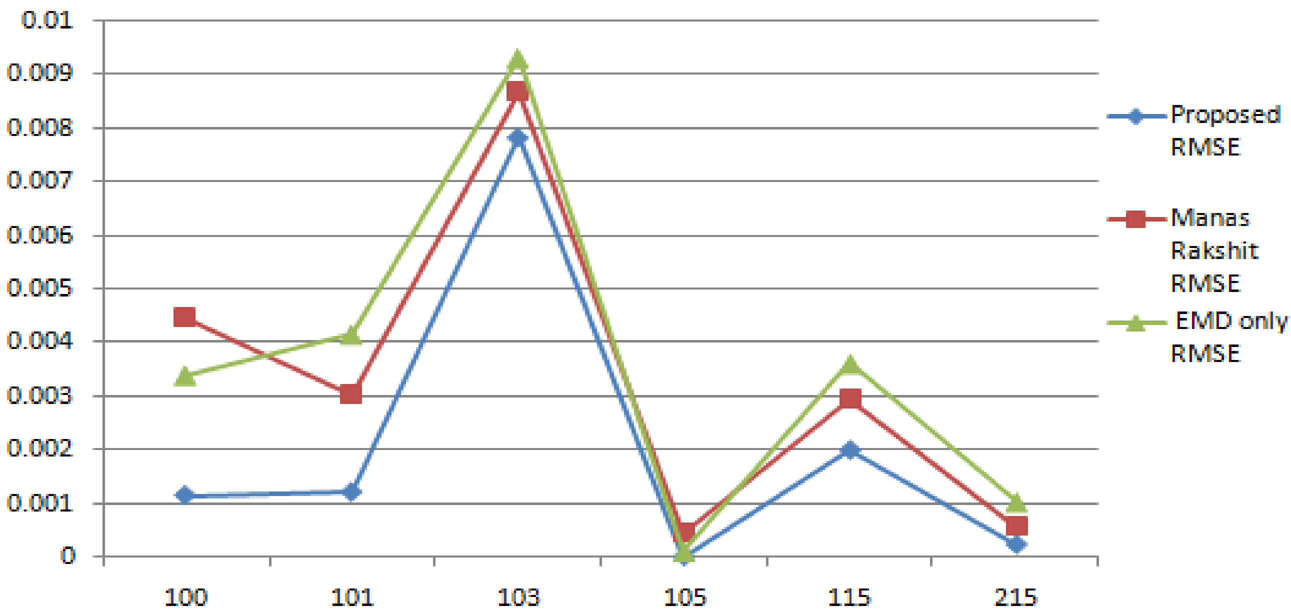

Figure 7 RMSE comparisons without external noise in MIT-BIH database.

IV-CONCLUSION

The proposed threshold & shrinkage function is useful while processing ECG signal & to improve signal-to-noise ratio (SNR) for obtaining clean recordings & preserve original shape for signal, especially peaks, without distorting waves &

segments. main job is to recover a true ECG signal from noisy recording & successfully achieved by proposed method. This thesis work is study of EMD based ECG signal de-noising and three research work have been studies and explained it's been observe that most of the available methods for ECG noise removal use EMD for ECG signal decomposition and later on different methods use different filters like [1] use switching mean filter [2] use adaptive filter and [3] monitor activity and normal FIR filter RMSE, SNR, PRD and standard deviation has been used for measurement of the results of the ECG signal filtering.

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