ECG DENOISING BASED ON EMD FOLLOWED BY MEDIAN FILTER

A Dissertation submitted towards the partial fulfillment
of the requirement for the award of degree of

Master of Technology
in
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Submitted by

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CERTIFICATE

This is to certify that the dissertation title "**ECG Denoising Based on EMD Followed by Median Filter**" submitted by **Mr. Sandip Shaw, Roll. No. 2K15/SPD/15**, in partial fulfilment for the award of degree of Master of Technology in "**Signal Processing and Digital Design(SPDD)",** run by Department of Electronics & Communication Engineering in Delhi Technological University during the year 2015-2017, is a bonafide record of student's own work carried out by him under my supervision and guidance in the academic session 2016-17. To the best of my belief and knowledge the matter embodied in dissertation has not been submitted for the award of any other degree or certificate in this or any other university or institute.

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DECLARATION

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ABSTRACT

ECG records the electrical activities of the heart and provides the important information which helps in detecting the cardiac abnormalities. But during the ecg acquisition & transmission of signal various type of artifacts or noise such as electromyography (EMG) noise, additive white gaussian noise(AWGN), powerline interferences noise, electrodes contact noise etc get contaminated with the ECG signal and corrupt the main signal. So the ECG signal must have to free from noises for accurate diagnosis of the heart.

In this thesis different type of method are used in order to denoised the ECG signal. In this removal of noises is done by various method first by Empirical Mode Decomposition (EMD) followed by Median filter second EMD followed by moving average filter third by Ensemble Empirical Mood Decomposition (EEMD) followed by moving average filter and the last by EEMD followed by median filter. The proposed technique is an enhancement towards the existing EMD and EEMD based denoising algorithm. As ECG is non –stationary signal and EMD is adaptive and data driven so it is suitable for non stationary signal. For the purpose of reducing noisey ECG signal, it is decomposed into Intrinsic mode function(IMF).Using Lower values of IMF, higher frequency value of IMF are neglected before signals being reconstructed and this will be free form noise with higher degree of Signal to Noise Ratio(SNR). Parameter that are used for comparisons are SNR, MSE and Correlation-coefficient.

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CHAPTER ONE

INTRODUCTION

1 INTRODUCTION

This chapter is the preface to rest of the thesis. This chapter includes a brief introduction of ECG denoising followed by literature review which includes the most important contribution to the field of ECG enhancement. The remaining part of this chapter includes the thesis organization and objective of the thesis.

1.1 Introduction

The electrocardiogram (ECG) signals show the reflections of heart's conditions and hence any abnormalities can be figured out by analyzing the ECG signals. As these signals are the nonstationary, hence it can be very tedious even for a trained physician to do a proper diagnosis. Hence the application of computers came in to existence and researchers throughout the world are working on computational techniques that can assist in accurate analysis of the ECG signal. As noises may cause wrong interpretation of the ECG signals therefore preprocessing has to be done to enhance the signal quality of ECG signal for further processing. Mainly the two dominant artifacts that get contaminated with the ECG are

- high frequency noise that includes electromyogram noise (caused due to muscle's activity).
- motion artifacts (caused due to electrode motion) .
- channel noise (White Gaussian Noise introduced during transmission through channels)
- powerline interferences and the low frequency noise i.e, baseline wandering due to respiration or coughing.

Many techniques have been reported in the literature for ECG denoising that includes morphological filter to remove the MA Noise, adaptive algorithm

(RLS) , wiener filtering, wavelet transform (WT), advanced averaging technique, independent component analysis and BWT (bionic wavelet transform) showing better result over WT. Many of thes techniques assume that prior information of the signal or type of noise is available. But practically, it is not possible to obtain information of the signal or noise prior to processing. Hence, here EMD technique has been chosen for the denoising of ECG as it is an adaptive mechanism to decompose any signal that doesn't need the prior information and was introduced by Huang et al. Many works have been reported in the literature showing contribution of EMD in biomedical signal processing. EMD has also been used as a very powerful technique to denoise the ECG Signals.

In this thesis an enhancement to the existing EMD and EEMD based approach with an additional work including median and moving average filtering to improve the QRS quality has been introduced that shows good improved results for the denoising of the ECG signal for both real as well as synthetic noisy case and described in the next section. The database that has been used here for the simulation of various experiments for the qualitative as well as quantitative performances of the proposed algorithm is the MIT-BIH arrhythmia database.

1.2 Literature Survey

During the past few year various contribution has been made in literature relating to the denoising of the ECG signal. Among them many of them uses either time or frequency domain representation of the ECG waveform.

"Many techniques have been reported in the literature for ECG denoising that includes morphological filter to remove the MA Noise, adaptive algorithm (RLS), wiener filtering, wavelet transform (WT), advanced averaging technique, independent component analysis (ICA) and BWT (bionic wavelet transform) showing better result over WT".

Many works have been conceded for the scope of this report. A brief introduction to some of them are presented as follow:

- **Mashud Khan** et. al. in[1] proposed a wavelet based algorithim in which "Signal to Noise residue algorithm assumes that the noise adds to the raw ECG signal in linear fashion. The symmlet8 mother wavelet has been used for multi-scale decomposition of the signal which enables accurate estimation of noise and facilitate its removal with minimal computation."

- **P Raphisak** et. al. in [2] proposed an automatic algorithm for discover EMG noise which is presented in the large ECG signal data. His proposed algorithm extract the EMG artifacts from the ECG signal by means of a morphological filters. EMG then identify by the locale of threshold of extracted EMG for the moving variance. The algorithm attain 100 % detection rates on the training data set. The algorithm is test on 150 test signal from 3 sets of test signal. Set one is obtain by sum of EMG noise to EMG free ECG signal and set two is yourself selected ECG section which include EMG noise and set 3 include randomly selected ECG signal. Sensitivity is 100 %, 94 % and 100 % on sets "one , two and three, respectively. Whole sets had 100 % specification. The algorithm used has Computational complexity of O(N)".

- **Chinmay Chandrakar.** et. al. in [4] proposed a technique in which a type of adaptive filter are used to overcome noise from the ECG signal such as PLI and Base Line Interference. In this technique Recursive Least Squares (RLS) are usede. The low frequency component & small features of the ECG signals are preserved for removing the artifact by proposed RLS algorithm. Least-squares algorithm try to minimize the addition of the square of the difference b/w the preferred signals & the model filters output .Once the "new sample of the incoming signal is receiving every iteration and the solution for the least-squares problem can be computed in recursive form which gives the result in the recursive least-squares (RLS)" algorithm. The RLS algorithm is "identified to pursue fast convergence even when the Eigen value spread of the input signal correlation" matrix is large. So these algorithm has good performance when they are used in time varying condition. All this advantage came with the increased cost of computational complexity and some stability problems which are not as critical in LMS-based algorithm.

- **Aswathy Velayudhan**. Et. al. in [5] proposed a new ECG signal denoising technique that are depend on Empirical Mode Decomposition (EMD) followed by Moving average filters and Discrete Wavelet Transform (DWT). Simulation is carried out with the help of the MIT-BIH database and the performance is calculated in term of standard metrics mainly signal to noise ratio (SNR), Mean Square Error (MSE) and Percent Root Mean Square Difference (PRD). The result confirm that the proposed technique provide a very good result for ECG Signal denoising.

- **SA Chouakri**. Et. at. in [6] proposed an algorithm that filter the noise from , real ECG signal. The usual wavelet ECG denoising method depend on the Donoho et al. algorithm that are appears at 4th level, obviously the P and T waves but the R wave undergoes considerable distortion. This is because of the interference of the white gaussian noise and due to the free noises ECG details sequence at level 4. To conquer this drawback their main idea is to approximate the corrupted white Gaussian noise & therefore removing the interfering noise, R wave at the 4th level detail sequence. The "denoised algorithm was applied to a set of the MIT-BIH Arrhythmia Database ECG records corrupted with a 0 dB WGN which provide an output Signal to Noise ratio of around 6 dB and an Mean Square error (MSE) values of around 0.0011". A comparative analysis using "the low pass Butterworth filters and the 4th level usual wavelet denoising provide the output SNR value of around 3 dB and MSE values of around 0.0018; which demonstrate the superior performances of our proposed denoising algorithm".

- **Manuel B. V**. et. al. in [7] proposed a technique that are based on Empirical Mode Decomposition (EMD). The input series are decomposed into a sum of intrinsic mode function (IMF) which represented an oscillatory mode. Whereas the delineations are used to preserves the QRS complex segment . Noisy IMF is selected by a moving adaptive window and excluded in the final reconstruction.

- **Allan Kardec Barros**.et.al.in [8] proposed a method that deal with the elimination of artifacts (electrodes, muscle, respiration, etc.) from the electrocardiographic (ECG) signal. In this used a method called independent component analysis (ICA) that blindly separates mixed statistically independent signal. ICA can separates the signals from the interferences, even if both are overlap in frequency. In order to estimate the mixing parameter in real time, proposed a self-adaptive step-size, derived from the study of the average behavior of those parameter, and a two-layer neural network.

- **D.Zhang** in [9] proposes an approach for baseline wander removal based on DWT. The shrinkage method uses E-Bayes posterior median to reduce the highfrequency noise. Symlet wavelet with order 8 is used for decomposition level upto 6 .

- **P.E Tikkanen** in [10] proposed a technique in which performance of different wavelet and wavelet packet based technique for noise removing simulated is considered with an electrocardiogram signals. A nonlinear denoising come up to is examine by relating soft & hard thresholding method in which the thresholding was selected using 4 different method. Coiflet wavelet & wavelet packet function are taken to construct the dyadic wavelet and optimized wavelet packet decomposition. This learning involve the quantitative comparison of different denoising approach through optimized error measure & visual examination of the denoised ECG signal and error signal. The "localization of the denoising error inside the cardiac cycle was study by visual examination of the denoised signal and extracting the error measures throughout the QRS complexs". The result prove that the wavelet denoised approach were normally additional efficient than wavelet packet approach in whole cases but with HEURISTIC SURE threshold choice rule as hard threshold for white noise is used. Denoised error tend to concentrated inside the QRS complex area when the wavelet approaches are employed and the soft and hard non linearities showed different balance in denoising the high-frequency part of ECG signal.

- **P. Mithun** et. al. in [11] proposed a denoising method based on wavelet. Their methods is advantage to the sense that it does not need a prior reference as in the case of adaptive filtering techniques. The discrete Meyer wavelet is selected as wavelet basis functions. A new thresholding funtions are also proposed which combine the feature of hard &soft thresholding.

- **Md. Ashfanoor Kabiret**.al.in [12] proposed a windowing technique in EMD domain. Distinct to the conventional approach this technique suggested to separate the QRS complex from the first three IMFs. The noisy signals after enhancement in the EMD domain, is then transform into the wavelet domain where an adaptive thresholding scheme is applied to wavelet coefficients. Then DWT are used to carry out adaptive soft thresholding after reconstructions to reduced the residual noises.

- **Omid Sayadi**.et.al. in [13] proposed a new ECG denoising technique in which a novel adaptive wavelets transforms bionic wavelet transform (BWT) is used, that have been first develop base on a model of the active auditory system. This have been some outstanding feature of the BWT such as high sensitivity, nonlinearity,concentrated energy distribution, frequency selectivity and the ability to reconstruct the signals via inverse transform but the most distinguishing characteristic of BWT is that “its resolution in the time–frequency domain can be adaptively adjusted not only by the signal frequency but also by the signal instantaneous amplitude and its first-order differential.” As well by optimized the BWT parameter parallel to modified a new threshold value one can handle ECG denoising with results comparing to those of wavelet transform (WT).

- **Wei Zhang** et. al. in [14] proposed a wavelet based subband adaptative filter algorithms that extract the weak ECG signals in a high noise environment. The hybrid approached to improved the extracted precision and provided a strong stability.

1.3 Objective

Electrocardiogram(ECG) signals show the electrical activities of the heart & provided the valuable informations which help in examine the patient’s heart conditions. On the other hand ECG signals area non stationary in nature and irregularity of the signal is not periodic but is noticeable at certain irregular interval during the day. So the clinical examination of the ECG take very more time. Due to the various artifacts sometime the useful information is lost. So the denoising of ECGs signals and computer based examination is done before diagnosis of the diseases.Very large variations in the morphology of ECG waveform is faced when analysis is done with automatic ECG. As well as we have also considered the time constraints. Thus the objective of the thesis is to come up with a simple algorithm which will denoised the ECG signal and remove the artifacts having less computational complexity without compromising with the efficiency .

1.4 Thesis Organization

This thesis contains five chapters including this chapter and remaining chapters is organized as follows:

Chapter Two : Introduction to ECG

In this chapter explanation of the ecg generation, ecg test, conduction system of heart, ecg waveform and ecg duration are given. Also the different artifacts that are contaminated with the Ecg signal during acquisition are also discussed.

Chapter Three : Proposed Method

In this chapter the algorithm or method that are implemented for the denoising of the ecg signal are discussed here. Also particular filter or adaptive window are used that are also discussed.

Chapter Four : Results and Discussions

This chapter contains all the results that are obtained according to the algorithm. Here the Ecg signal database that are taken from MIT BIH and noise generated accordingly are shown. Here we find the comparison result between noisy signal and denoised ecg signal.

Chapter Five : Conclusions

In this analytical remark to overall achievement & limitation of all the proposed work & scope for further research work in this domain are presented.

CHAPTER TWO

INTRODUCTION TO ECG

2 INTRODUCTION TO ECG

2.1 Overview

The electrical activities related to any muscle action travel during various tissues and ultimately reach to the surface of the body where it is detect by the electrodes applied to the skin. The records that obtain from the depolarisation and repolarisation voltage of the heart muscle are called an electrocardiogram or ECG.

Electrocardiogram(ECG) are used to measure the rate as well as regularity of heartbeats, size and position of the chambers and occurrence of the any damages to the heart. And the special effects of drugs or device that are used to control the heart such as a pacemaker.

ECG trace diagram are shown below. Each “5 mm” square in the grid represent the 0.2 second duration and “0.5 mV” amplitude. The trace shown in the diagram is 8 seconds in length, each second is “25 mm “(5 squares) long as indicate below by the black (arrowed) lines.

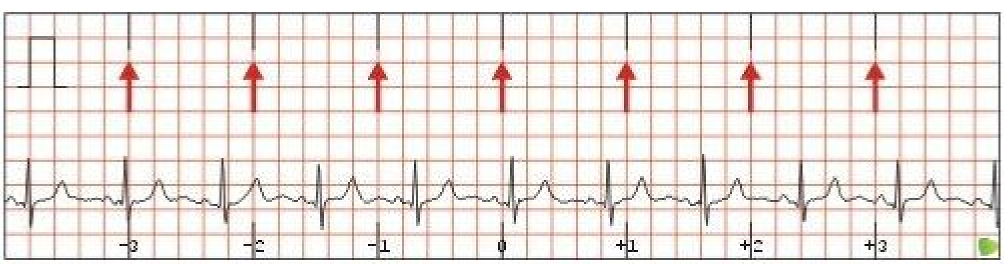


Fig:1 Electrocardiogram(ECG)

To classify the ECG in order to interpret and understand the ECG, particular terminology are used to define:

1. ECG duration

2. ECG waveform

ECG be able to be use to detect normal activities, cardiac arrhythmia and heart diseases. In oder to detect different cardiac problem ECG tests are used.

2.2 Conduction System of the Heart

Here we describe the action of the heart muscle in order to derivation of the ECG. Here the heart are influence through autonomic nervous system which can be going to increased or decreased the heart rate in line by means of the requirement of the body.

However due to the intrinsic regulating system(called conduction system) it can be possible used for the heart to do beating from the nervous system without any direct stimulus.

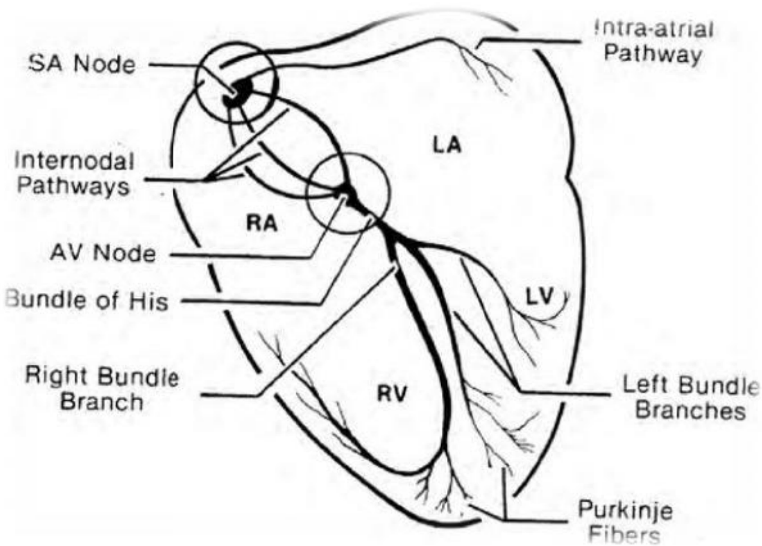


Fig:2 Conduction system of heart

The systems are composed of the special muscles tissue that are generated and distributed by the conduction that are cause contraction to the cardiac muscles. Then these tissues are going to found in the sinus (sinoatrial node) node, atrioventricular node bundle, bundle branches and conduction myofibres.

When this is stimulated by the electrical activity muscle fibre contract and produced the motion. So this electrical activity are called as depolarisation in the heart system. The contraction that occurred to be caused the blood to be pumped through out the body and contract chamber inside the heart are called “systolic”. Eectrically repolarisation causes the heart to be relaxed. Relaxed chamber inside the heart are called diastolic.

2.3 ECG Waveform

Every section of the heartbeat produce a different deflection on to the electrocardiogram (ECG). Then the deflection are recorded as the series of positive & negative waves. On the normal ECG waveform there are typically of five visible waveforms:

- P wave
- Q wave
- R wave
- S wave, and
- T wave

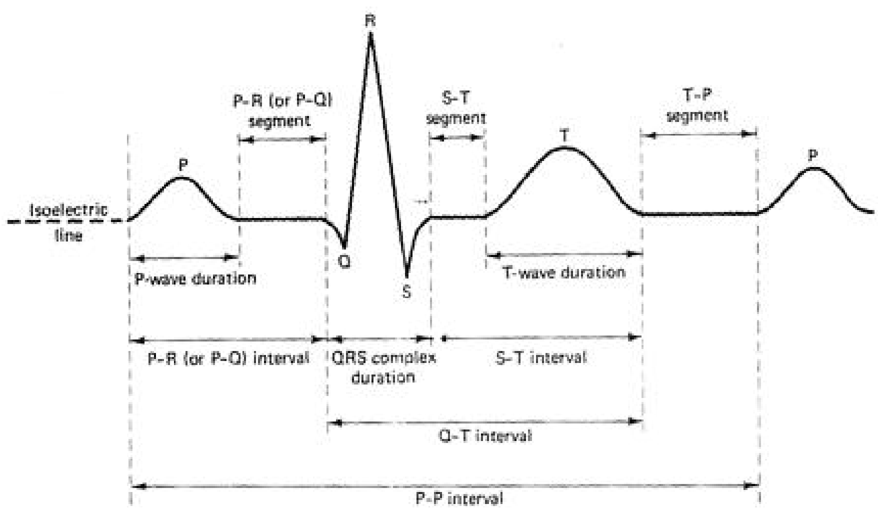


Fig:3 ECG waveform

The P Wave

P wave is the first deflection of the heartbeat which is small upward wave. P wave indicate the atrial depolarisation. and the early portion of the P wave are largely the reflection of the right atrial depolarisation ,where as the terminal portion are largely a reflection of the left atrial depolarisation. The fraction of a second after the P wave is begin to the atria contract.

The P waves that should be all look alike and this can be no larger than “0.3mV”. The taller morphologies shall be indicated as a right atrial enlargement and the wider ('m-shaped') morphologies can be caused by the left atrial enlargement.

Several P waves are seen by the second and the third degree blocks.

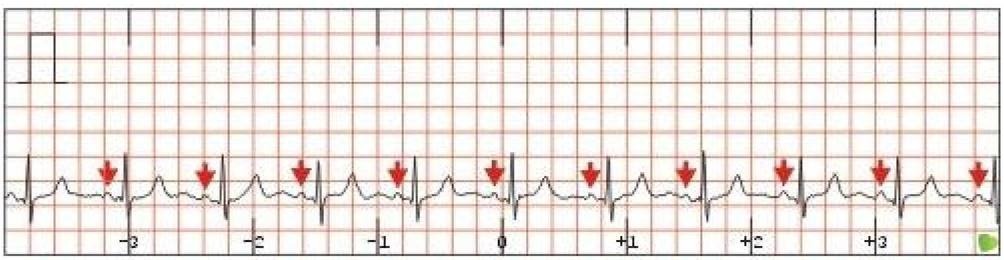


Fig:4 The P wave

The Q wave

After the P wave the Q wave are the any initial downward deflections. The normally Q wave represent the septal depolarisation.

The Q wave that are seen followed the heart attack can be “wide and deep”. The dead muscles of the heart can neither beconduct nor produce current so the electrocardiogram (ECG) pick up the current flows away from this muscles to produce a strong negative deflections

Fig:5 The Q wave

The R wave

After the P wave even when the Q waves are absent the R wave is the first upward deflection. The R wave of the ECG are normally the easiest waveform that recognize on the electrocardiogram and represent early "ventricular depolarisation".

These R wave of ECG can be enlarge with the ventricular hypertrophy as a thin chest wall otherwise with the athletic physique. It can be reduce by the range of mechanism including obesity.

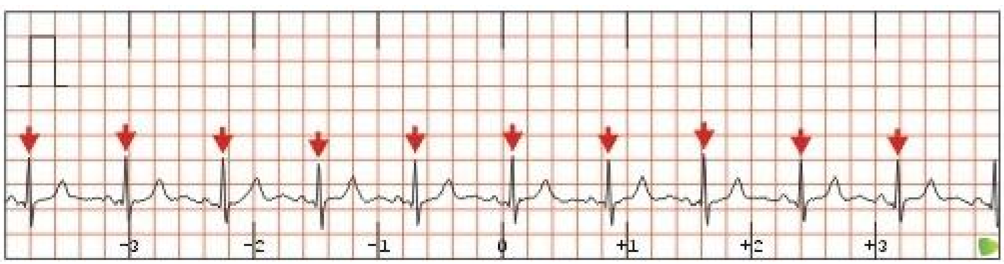


Fig:6 The R wave

The S wave

After the R wave, S wave are the first negative deflection and it represented the late ventricular depolarisation.

Fig:7 The S wave

The T wave

T wave represent the repolarisations of the ventricles and is normally upright, slightly asymmetric and somewhat rounded. Its structure will be alter with the digitalis toxicity and breath holding.

The T wave can be flat or inverted with the myocardial ischaemia, ventricular hypertrophy, bundle branch block and ventricular ectopic beat. The T wave is peaked and tall with the hyperkalaemia that is “potassium decreases with the durations of the refractory periods and enhances repolarisation”.

The T wave is notched and flat with condition such as pericarditis, flat cardiomyopathies, and hypothyroid with hypokalaemia.

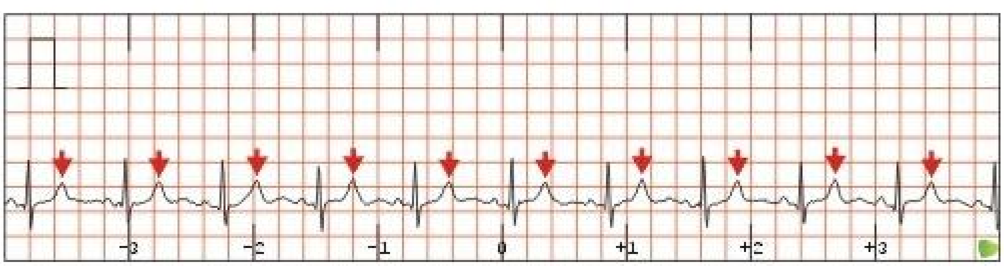


Fig:8 The T wave

2.4 ECG Duration

The Electrocardiogram (ECG) split into the different segments (as shown in figure 3) and the intervals which are related directly to the phase of cardiac conduction. Then the Limit can be set on these from which to diagnose the deviation from normality.

The main propagation of ECG characteristics are as follows:

- QRS complex
- PR segment
- PR interval
- ST segment
- RR interval, and
- QT interval

PR Interval

The PR interval of ECG begin at the onset of the “P wave” and end at the onset of the “QRS complex”. This PR interval represent the time that the impulse from the sinus node takes to reach the ventricles. It is called as PR interval because the Q wave may be absent. Normal value lies between “0.12” and “0.20” sec.
Whereas the ventricular pre excitations are due to the accessory pathway which bypasses the atrioventricular nodes and the durations of the PR interval will be shorten. The Value of less than “0.12” seconds are called as short PR interval.

Duration with ectopic beats may occur in PR interval because the impulse does not have as distant to travel.

If the PR interval of ECG is greater than “0.20 second” then the first degree atrioventricular blocks are diagnosed.

The PR interval will be progressively increased with the Wenckebach phenomenon.

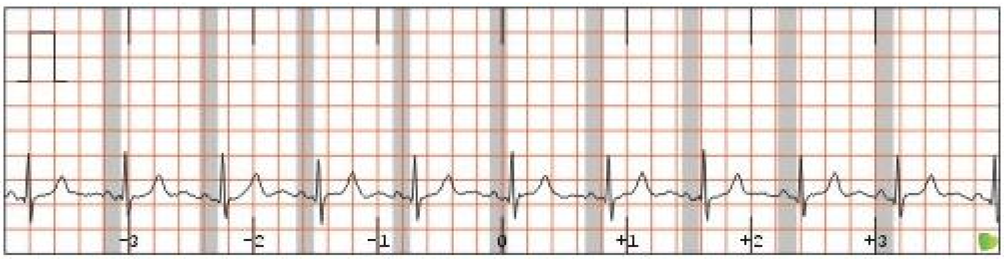


Fig:9 PR interval

PR Segment

The PR segments start at the endpoint of the P wave of ECG and finish at the arrival of the QRS complex. It represent the period of the conduction from the atrioventricular node to down the bundle of his and through the bundle branche to the muscles. The PR segment can be considered as a representing ventricular diastole, isoelectric and atrial systole but may be deviated in the presence of atrial injury.

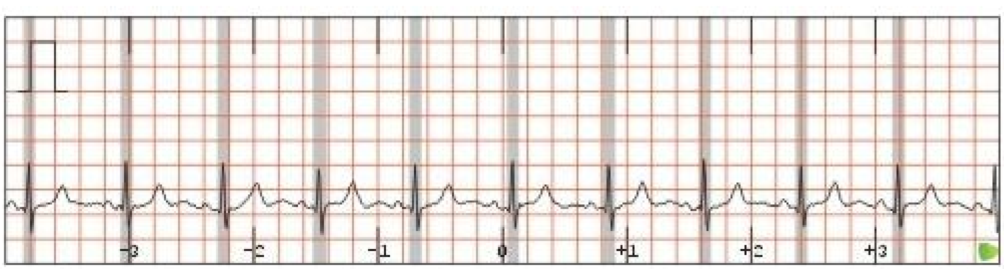


Fig:10 PR Segment

QR Complex

The QT interval of the ECG waveform represent the duration to repolarisation from the depolarisation of the ventricles and it begin at the beginning of the QRS complex and finish at the endpoint of the T wave of the ECG duration. The duration of the QT interval vary with, gende, age and heart rate.

Short QT interval are seen with the hyperkalaemia , hypercalcaemia, hyperthyroidism, class IB drugs and digitalis toxicity.

Long QT interval are seen with the slow heart rates, hypokalaemia, myocardial disease, myocarditis congenital heart disease, hypocalcaemia coronary heart failure class IA and III drugs and anorexia.

Long QT interims increment the danger of ventricular ectopic beats. Stops are a potential arrhythmogenic component with delayed QT interims for ventricular tachycardia, and specifically, torsade de pointes (a polymorphic ventricular tachycardia) which may prompt sudden cardiac death.

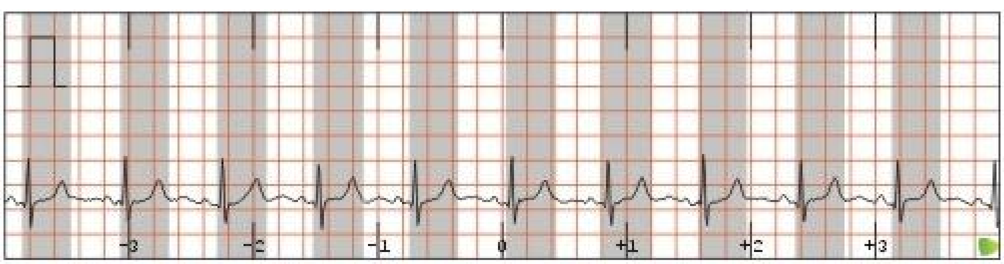


Fig:11 QRS Complex

ST Segment

The ST segment begin at the “endpoint” of the S wave(as seen in the fig.3) and end at the “onset” of the T wave.

The atrial cells are relaxed during the ST segment and the ventricle are contract so that the electrical activities are not visible the ST segments are normally isoelectric.

The ST segment depression can be occured when the ventricle is being starved of oxygen ("normally due to blocked arteries"). This is called as myocardial ischaemia.
The ST segment are elevated occured with the recent pericarditis, cardiac injury Prinzmetals angina and ventricular aneurysms.

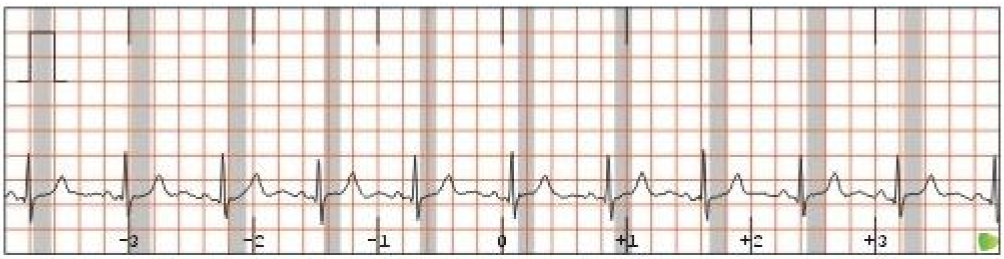


Fig:12 ST Segment

RR Interval

Between the R wave of the one heartbeat and R wave of the preceding heartbeat are the time measurement of the RR interval.
RR interval is normally regular but it may be irregular with the sinus node disease or supraventricular arrhythmia.

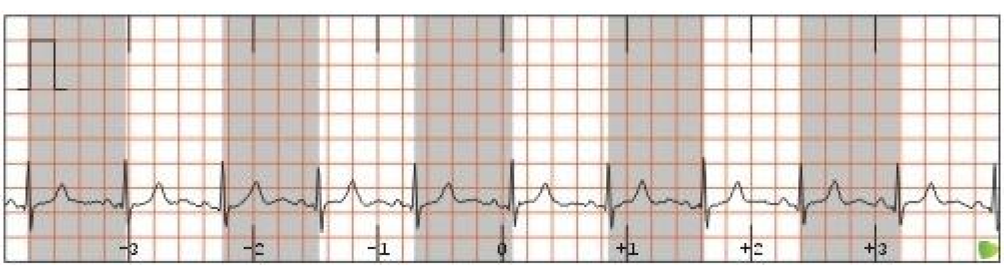


Fig:13 RR Interval

2.5 ECG Noise and Artifacts

As we know ECG signal are the non-stationary and it is very tedious even for the trained physicians to do proper diagnosis. As noise can causes wrong analysis of the ECG signal so proper preprocessing have to be done to enhanced the signals quality of the ECG signal for further processing. There are mostly two central artifact that are get infected the ECG signal are electromyogram noise that are high frequency noise which are caused due to the muscle's activity, channel noise that is white Gaussian Noise which is introduced during transmission through channels, motion artifact that is caused due to the electrode motion and powerline interferences that are low frequency noise that is baseline wandering which is caused due to respiration and coughing.

Here the list of some noise which are affected the ECG signal are:

- Motion Artifact
- EMG Noise
- Power Line Interferences
- Electrodes contact noise
- Instrumentation Noise

Motion Artifact

Baseline change of motion artifact that are caused by electrodes motion. There are some usual cause of motion artifacts like, movement, respiration and vibrations of the subject. The peak amplitude or duration of the artifacts are random variables which depend on the variety of unknown such as electrolyte properties that is if one is used between the electrode and skin, the electrode properties, skin impedance and the movements of the patient . The baseline drift that are occured at unusually low frequency i:e approximately less than 1Hz of ECG signal.

EMG (Electromyographic) Noise

Electromyographic(EMG) noise are cause by the contraction of other muscles besides the heart . But when the other muscles of the body in the locality of the electrode contract they get generated by repolarisation and depolarization wave that can be picked up by the Electrocardiogram. The extented of the crosstalks depend on the amounts of muscular contraction i.e subject movement, and the quality of the probes . It is well established that the amplitude of the Electromyographic(EMG) signals are random (stochastic) in the nature or it can also be reasonably modelled by a Gaussian distribution function . Signal mean of the noise may be assumed to be the zero and, the variance are depend on the environmental variable or will be changing depend on the conditions of the signal. Some studies has been shown that standard deviation(SD) of the noise is typically 10 percent of the peak to peak ECG amplitude . Whereas the statistical model are not known and it could be note the electrical activity of the muscles throughout the period of the contraction that can generated on the surface potential. The frequency of the Electromyographic(EMG) noise is in the range of 100 to 500 Hz.

Power Line Interference Noise

It occurs all the way, through two mechanisms, inductive and capacitive coupling. Capacitive coupling refer the transfering of energy among, the two circuit by means of a coupled capacitance present among the two circuit whereas value of coupling capacitance decreased with increased separation between the circuits. On the other hand Inductive coupling are caused by the mutual inductance among two conductor and when the current flow throughout the wire it produced a magnetic flux which may induced a current in the adjacent circuit. "The conductor that determine the separation among them are determined by the values of the mutual inductance; and the degree of the inductive coupling. Capacitive coupling are more responsible for the “high frequencies noise” but inductive coupling establish the low frequencies noise. That’s why inductive coupling are more dominating mechanism. So to bound the quantity of power line interference we have to keep in mind that electrodes are applied properly or not; so that there is no loose wires anymore, or all component should have adequately shielded.

Electrode Contact Noise

The key mechanism resulted in baseline disturbance that is “electrode-skin” impedance variation. If the electrode-skin impedance is larger than smaller the relative impedance, changes need to caused the main shift into the baseline of Electrode contact noises are cause by means of variation in the location of the heart w.r.t the electrode & change in the propagation medium among the heart and the electrode. This may cause sudden change in the “amplitude” of the electrocardiogram signal and “low frequency” baseline shifts. Additionally poor conductivity among the electrode & the skin reduce the amplitude of the Eletrocardiogram signal & increase the probability of disturbances by reducing Signal to noise ratio.

The electrocardiogram signal. It can’t be possible to detect the signals characteristic consistently in the presence of body movement if the skin impedance are extraordinary high. Therefore unexpected change in the skin electrodes impedance induced spiky baseline transient that decay exponentially. This noise-signal characteristic included the amplitude of the initial transition & the time constant of the decay.

Instrumentation Noise

Noise also contributed from the electrical equipment that are used in ECG measurement. The main sources noise are from the cables, electrode probes, analog-to-digital converter and signal processor or amplifier. Unluckily these noise can’t be eliminated because it inherent in the electronic component, but these noise can be reduce by higher quality equipments or careful circuits design. Unlike from this another form of noise which termed as “flicker noise” which is very significant in Electrocardiogram measurement because of the low frequency contents of Electrocardiogram data.

CHAPTER THREE

PROPOSED METHOD

3 PROPOSED METHOD

3.1 Overview

In this chapter we will describe all the algorithm which are implemented in this thesis for denoising of electrocardiogram signal. In this project an Empirical mode decomposition (EMD) and Ensemble Empirical mode decomposition (EEMD) based approach with an additional work including median filter and moving average filter are used to improved the QRS quality, that shows good improving result for ECG signal denoising for both real and synthetic noise cases.

3.2 Empirical Mode Decomposition

Huang et al developed the Empirical Mode Decomposition (EMD) [15] for the prosperous method to analyze non-stationary or nonlinear data by decomposing into a set of finite data and frequently small number of imf i:e "intrinsic mode function" that should follow two conditions:

- the number of zero crossing and local extrema should be equal or be different by at most one.
- the mean value of the local maxim and the local minima must be zero at any point of the time.

The decomposition technique merely use the envelope outlined by the native maxima and minima severally when finding the extrema, associate degree higher envelope are created by connecting all the native maxima by a cubical spline line. Equally the lower envelopes are created by all the native minima. Currently their means are calculated and also the distinction among the signals information & this mean are found and explicit due to the 1st part shown as:

$$p_1(t) = x(t) - q(t) \tag{1}$$

Where *x(t)* is the signal *q(t)* is the mean of the lower and upper envelope *U(x)* and *L(x)* respectively that is:

$$q(t) = \{U(x) + L(x)\}/2 \tag{2}$$

At this time the condition of the IMF are check for the components *p1(t)* and on fulfilling the condition for IMFs it become the first IMF or else the procedure is repeat till the IMFs are founded. This method of finding the IMF to eliminating the ride wave or make the waves further symmetric are called sifting process. The "sifting process" are repeat until the proto- IMF $p_k(t)$ until the first IMF *I*1*(t)* is achieve and are closed by a define standard termed as Sum of Difference which is denoted by "D" and set in between 0.2 to 0.3 [15] and is given by:

$$D = \sum_{t=0}^{T}\left[\frac{\left|p_{1(k-1)}(t) - p_{1k}(t)\right|^2}{p_{1(k-1)}^2(t)}\right] \tag{3}$$

"When the calculated value for "D" is smaller than the defined threshold then the first IMF *I1(t)* is obtained and is specified as":

$$x(t) = I_1(t) + R_1(t) \tag{4}$$

$R_1(t)$ termed as residue that contain informations of the longer period component. These method of practice repeat on all these subsequents *Ri(t)*s and the result are acquired like:

$$R_1(t) = I_2(t) + R_2(t) \text{ , or} \tag{5}$$

$$R_{m-1}(t) = I_m(t) + R_m(t) \tag{6}$$

When this residue $R_m(t)$ become monotonic function and constant the sifting process will stopped. Therefore after adding equation (4) and (6) we obtain the result as:

$$x(t) = \sum_{i=1}^{m} I_i(t) + R_m(t) \tag{7}$$

Where $I_i(t)$ represent the ith order IMF and $R_m(t)$ represent the final residue.

EMD is different from other signal processing techniques *eg* .wavelet, spectrograms, etc. and it is used in the analysis of non-linear and non-stationary signals.The IMPs obtained in EMD will act as a filter bank and are the major tools in the removal of noise from ECG. But the EMD method is very sensitive to noise . The two major drawbacks of the EMD method are mode mixing and scale separation. Both of these drawbacks were removed by a new technique EEMD proposed by Huang *et al.*

Drawback of EMD

A) Mode Mixing

In the case of Mode mixing an IMF can represent false information about the physical process. The IMF ceases to have physical meaning about actual physical process. This problem occurs when IMF consists oscillations of dramatically mismatched scales. These disparate scales are caused by intermittency of driving mechanisms[1]. This drawback was alleviated by proposing an intermittence test in case of EEMD.

B) Scale Separation

The intermittence test algorithm only works weeI if there are clearly separate and subjectively defined time scales in the data . This drawback was overcome by EEMD as it is a noise-assisted data analysis method.

3.3 Ensemble Empirical Mode Decomposition

EEMD gives true IMFs(IMF-) as the mean of the corresponding IMFs obtained via EMD over an ensemble of trails, generated by adding different realizations of white noise of finite variance to them original signal x[n] [1]. EEMD algorithm can be described as:

1. Generate $x^i[n] = x[n] + w^i[n]$, where $w^i[n]$ (i =1 .. ...., I) are different realizations of white Gaussian noise.

2. Each $x^i[n]$ (i = 1; : : : ; I) is fully decomposed by EMD getting their modes $IMF_k^i[n]$ where k = I,..,K indicates the modes.

3. Assign IMF_k^- as the k-th mode of x[n]; obtained as the average ofthe corresponding

$$IMF_k^i : \ IMF_k^-[n] = \ IMF_k^i[n] \ /I$$

So for each one a residue is obtained as

$$r_k^i[n] \ = r_{k-1}^i[n] \ - IMF_k^i[n]$$

The amplitude of white to be added also plays an important role . If the amplitude of the added noise is too small relative to the original signal no effect on mode mixing prevention can be achieved, on the other hand if it is too large it would result in redundant IMF components.

Moving Average Filter

The moving average filter is a simple Low Pass FIR (Finite Impulse Response) filter commonly used for smoothing an array of sampled data/signal. It takes M samples of input at a time and take the average of those M-samples and produces a single output point. It is a very simple LPF (Low Pass Filter) structure that comes handy for scientists and engineers to filter unwanted noisy component from the intended data.

As the filter length increases (the parameter M) the smoothness of the output increases, whereas the sharp transitions in the data are made increasingly blunt.

This implies that this filter has excellent time domain response but a poor frequency response.

The MA filter perform three important functions:

1) It takes M input points, computes the average of those M-points and produces a single output point
2) Due to the computation/calculations involved , the filter introduces a definite amount of delay
3) The filter acts as a Low Pass Filter (with poor frequency domain response and a good time domain response).

Median Filter

The median filter is a nonlinear digital filtering technique, often used to remove noise from the signal. Such noise reduction is a typical pre-processing step to improve the results of later processing. It is better than moving average filter because it is less sensitive to outliers.

For Example: To demonstrate, using a window size of three with one entry immediately preceding and following each entry, a median filter will be applied to the following simple 1D signal: $x = (2, 80, 6, 3)$.

So, the median filtered output signal y will be:

$y_1 = \text{med}(2, 2, 80) = 2,$

$y_2 = \text{med}(2, 80, 6) = \text{med}(2, 6, 80) = 6,$

$y_3 = \text{med}(80, 6, 3) = \text{med}(3, 6, 80) = 6,$

$y_4 = \text{med}(6, 3, 3) = \text{med}(3, 3, 6) = 3,$ i.e. $y = (2, 6, 6, 3)$.

3.4 Proposed Method for ECG Signal Denoising

In this project present work is devoted towards the Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) based mostly denoising of cardiogram signals and any enhancements are created to the present rule that show elegant improve result for the denoising of the cardiogram signals. Below presented the block diagram of the proposed algorithm:

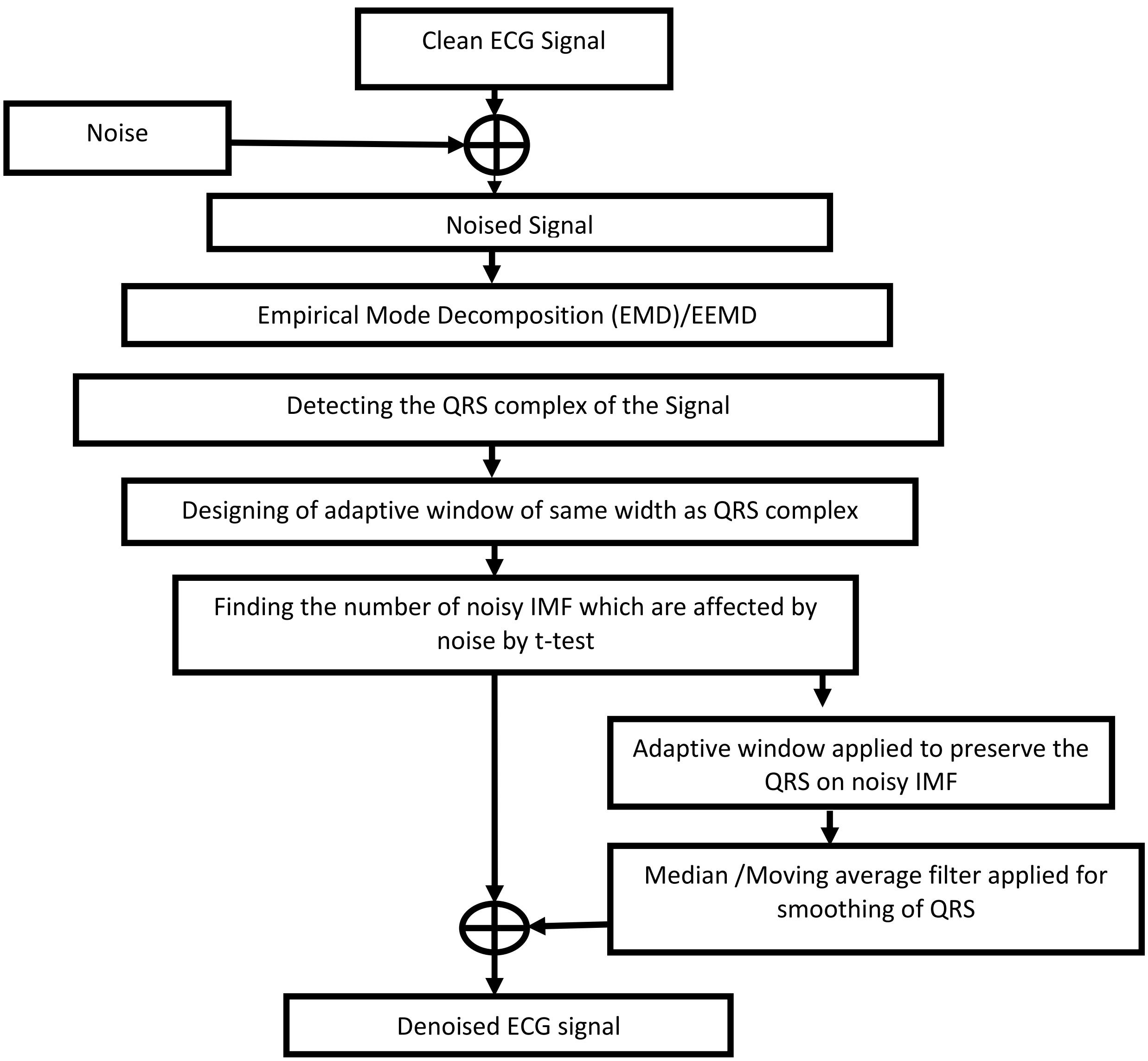


Fig-14: Block diagram of Proposed Method

Proposed method can be explained in following steps:-

3.4.1 Noisy ECG Signal Decomposition

The EMD is applied to the Noisy ECG signal to get a series of IMFs representing different oscillations .

3.4.2 QRS complex detection

To preserve the QRS complex we need a description of the QRS complex. Fig. 13 and 14 shows the plot of the ECG signal for clean and noisy ECG signal respectively . It is clear from these figures that these figures reveal that the width of the QRS lie within the two zero crossing points with one zero crossing point in the left hand side of the local absolute minima and another one at the right hand side of the local absolute minima .

Here word absolute has been included due to the fact that sometimes in the case of noisy ECG signal the local minima may lie just near the R-peak (fiducial point). As noise changes the shape of the actual signal, and will create a huge delusion for the actual width of the QRS complex . It has been observed by performing various experiment for both synthetic as well as real noise cases and for the noisy ECG signal (record 103) having white Gaussian noise with 10 dB SNR it is shown in Fig. 14 . It is observed that the width of the QRS complex will be lost if the local minima is considered whereas the choice of taking local absolute minima solves this problem of misinterpretation for the actual width to be preserved . As we are dealing with the discrete time signal, thus many times it is not possible to have the sample value at exact zero crossing point .

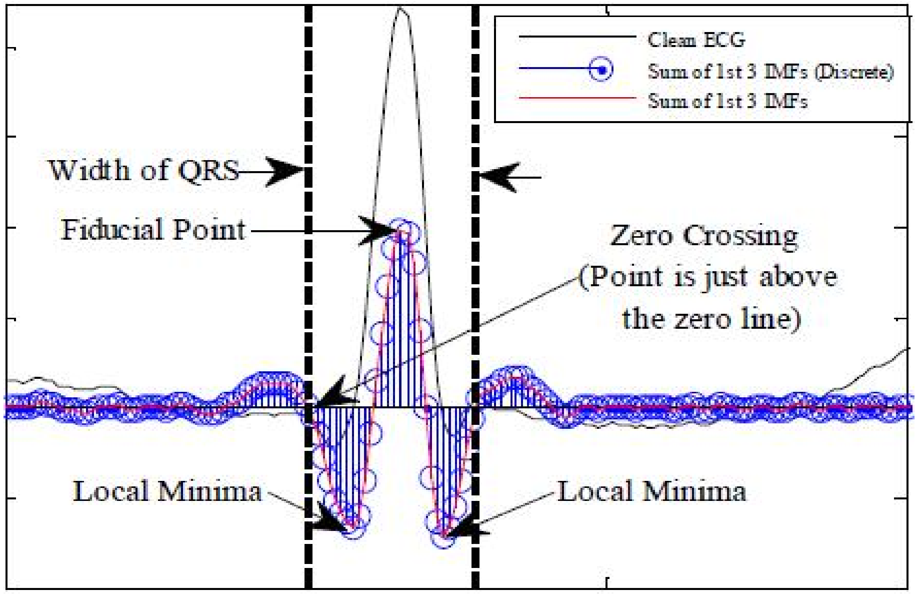


Fig: 15 Duration of the QRS complex by taking zero crossing point on both sides of the local absolute minima of the fiducial point of the clean ECG signal .

3.4.3 Finding Width of QRS Complex

Hence to preserve the QRS complex we have to find out the width of it and it can be found by following steps :

- Identification of the R-peaks (fiducial points)
- Applying EMD to the noisy ECG signal
- Finding of two local absolute minima on both sides of the fiducial points
- Detection of the zero crossing points on the LHS of the left absolute minima and on the RHS of the right absolute minima (here in case of absence of exact zero crossing point the just above the zero crossing point is to be considered), which makes the complete width of the QRS complex.

Here the fiducial points(R-peak) are assumed to be known, as the experiments are performed on the data taken from the MIT-BIH arrhythmia database that includes the annotation signals and has been used here.

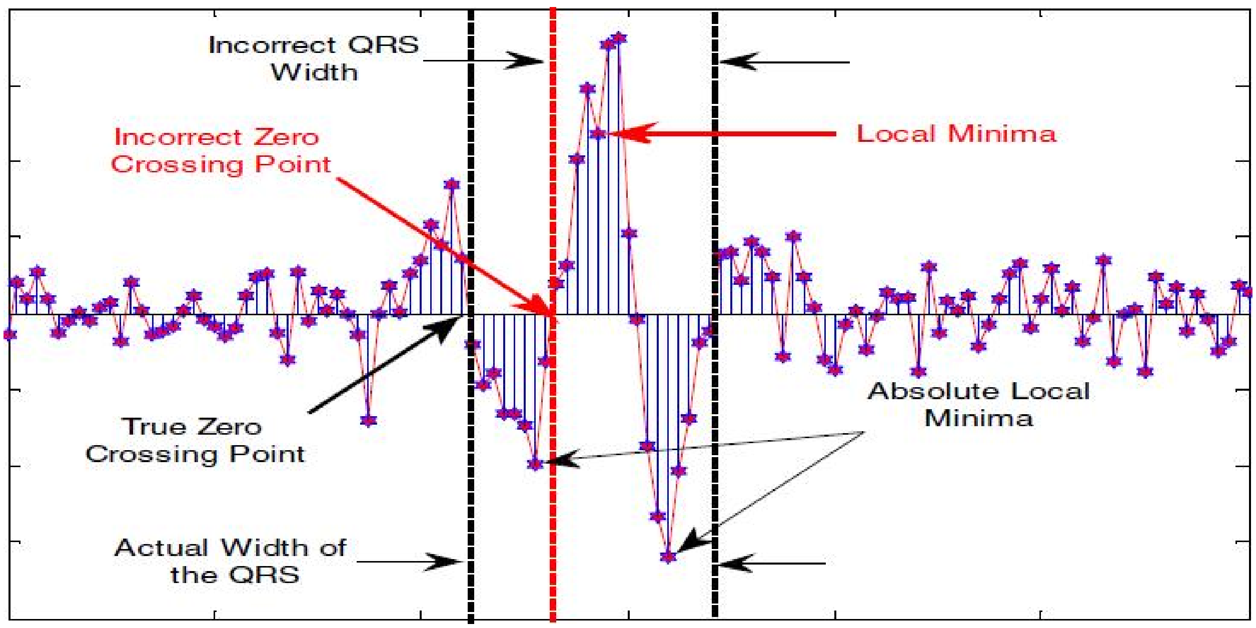


Fig: 16 Duration of the QRS complex by taking zero crossing point on both sides of local minima of the fiducial point of the noisy ECG signal differ by actual QRS width and is achieved by the absolute local minima.

3.4.4 Adaptive Window Designing for the QRS complex

To preserve the QRS complex from the noisy IMFs an adaptive window is designed and width of window is varied according to the width of each QRS complex in the IMFs . The magnitude of the window is kept unity within the width of the QRS complex . The window is selected as the Tukey window (tapered cosine window) given as :

$$(t) = \begin{cases} 1/2[1 + cos\left(\Pi \frac{|t|-t_1}{t_2-t_1}\right); & t_1 \leq |t| \leq t_2 \\ 1\,; & |t| < t_1 \\ 0\,; & |t| > t_2 \end{cases} \tag{8}$$

Where, t_1 denote window limits for unity amplitude and t_2 refers to the limit for transition region. Throughout the $2t_1$ regions magnitude remain unity of the window that means that the windows will bypass any values, inside that region and hence if $2t_1$ equal to the QRS-complexs without any distortion it will preserved, here t_2 is consider as the transitions widths that allow several additional portions of the signals are passed with spiky attenuation & save QRS-complex for some distortions. Therefore to preserves the QRS-complexs in (8) the flat regions widths $2t_1$ are taken to be equals to QRS-complexs widths that determines by the technique which is describe in the sub section**.** Since the spreading of the oscillatory pattern around the QRS complex increases with the increasing order of the IMF.

Since the transitions regions must also be varying accordingly & are achieve by defining a proper ratio, of one way transitions regions length that is $|t_1 - t_2|$ and flatness regions should length $2t_1$ i;e □ = $|t_1 - t_2|\ /2t_1$, where □ is taken as free parameter. As a result of performed various experiment □ is assumed to be 30 percent for the first IMF & then for further IMF it will be I x 30% (I: order of IMF); so the spreading of the windows accordingly to the QRS-complex in increased IMF order.

3.4.5 Finding the number of Noisy IMF

To apply the window for preserving the QRS-complexes, we have to first know the numbers of IMF which are ontributing to high frequency noise as QRS complexes are also high frequency contents of the ECG signals that are mostly remain in the starting lower order of IMF which are previously corrupted with the noise. As ECG signal of corrupting noises are usually of zero mean but the ECG signals are generally of non-zero mean. So from this fact it is easy to separate the noisy signals and ECG signals in the EMD domains. Noises are mostly present in the lower order of IMF thus here statistical test are applied to a particular combination of IMF for their noise testing by checking for the zero-mean. Among the entire statistical test, the t-test is frequently used for finding the noise order. The reason behind selecting this t-test is that it checks for the zero mean of the signal having unknown variance. Two hypothesis of t-test i.e, null hypothesis and alternative hypothesis testing are used for finding the number of noisy IMF that are as follows:

$$H_0 : mean(H_{PS}^{N}(t)) = 0\ ; null\ hypothesis$$

$$H_1 : mean\left(H_{PS}^{N}(t)\right)\ \neq 0\ ; alternative\ hypothesis$$

Here the significance level is being used is 5% so that the null hypothesis at 5% significance level is rejected to come close towards the alternative hypothesis. For finding the number of noisy IMF we apply the t test to $H_{PS}^{N}(t)$ for N = 1, 2,…. until the alternative hypothesis is accepted. When $H_{PS}^{nt}(t)$ is the partial sum,that accept alternative hypothesis then *nt* is the number of IMF that is dominated by noises. Sometimes it may possible that the ECG signal is having mean near to the zero, for the noisy IMFs can caused over the smoothing. Therefore to overcome with this we are considered that the high frequency noises are mainly present in the starting IMF on applying EMD. Since the maximum noises are present in the starting five IMFs as after that a very little or absolutely no noise is present. Hence we considered the number of IMFs contributing to the noises as: *n =min(nt, 5)*; where, *nt* is the number of noisy IMFs incurred from the t-test applied as above. Hence the over smoothing problem is debarred by selecting this approach.

3.4.6 Preserving the QRS Complex by applying window

After finding the number of noisy IMFs, to preserve the QRS complex from them the window is applied to these IMFs. For each IMF to preserve the each QRS complex, the window function is established by the concatenation of window formed in (6) such that it is centered at the fiducial point of each QRS in the IMF. The window function to be applied is as follows:

$$F_p(t) = \sum_{q=1}^{N_q} TW_{pq}(t) \tag{9}$$

where; *p = 1 : n*, and n is the number of noisy IMFs, N_q is the total number of QRS complex in each IMF, where $TW_{pq}(t)$ represent the window of variable size for the *qth* QRS complex in the *pth* IMF as the QRS complex is not fixed and can vary throughout. On applying this window function to all the noisy IMFs, only QRS width will be preserved and other than this everywhere we will get a sharp change to zero. To avoid this sudden change and to preserve the remaining information if any we applied a complementary window to these noisy IMFs with a very less attenuation factor.

3.4.7 QRS Complex Smoothing

After applying the window to the noisy IMFs the QRS complexes are preserved within their boundary. However due to noises the shape of the QRS complex is changed and some peaks get embedded within it, that make changes in the biphasic or triphasic shape (the actual feature) of the QRS complex. Thus to get a noise free ECG signal, smoothing of the QRS complex is done. Smoothing of the QRS complex is done after the partial reconstruction of the signal i.e, by adding the windowed IMFs together so that the QRS complex is reconstructed after the removal of noises.

Now smoothing of this is done by the median filter and moving average filter technique, because it will smooth the signal (here mainly QRS complex) by taking the mean of its three neighboring samples which will suppress the additional peaks by making it close to the actual shape without attenuating the amplitude of the R-peak. In this technique, each sample in the signal gets replaced by the mean value of its neighboring samples defined in the span, and the span must be odd and it keeps the end point unchanged.

The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most obvious window is just the first few preceding and following entries. Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median.

3.4.8 Reconstruction of the signal

To obtained the denoised ECG signal the reconstruction of the signal is done by adding the smoothed window signal and the remaining IMF of the signal.

CHAPTER FOUR

RESULTS & DISCUSSIONS

4 RESULTS & DISCUSSIONS

This chapter contains all the results that are obtained according to the algorithm. Here the Ecg signal database that are taken from MIT BIH. Here we find the comparison result between noisy signal and denoised ecg signal and also SNR, MSE and Correlation Coefficient parameters are calculated.

4.1 Quantitative Analysis

Various experiment are taken and the performance of the proposed algorithm is evaluated in terms of the Mean Square error, Correlation coefficient and Signal to Noise Ratio. The Noisy Ecg signal (ECG recording 103) before denoising is represented in figure 17 .

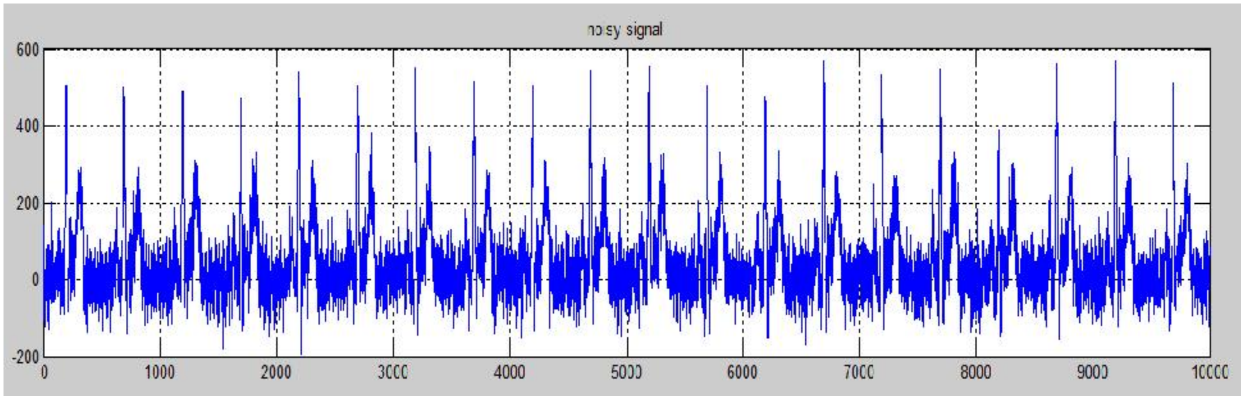


Fig: 17 Noisy ECG signal

When the EMD/EEMD are applied to the noisy ECG signal it decomposed into several IMF, then the number of noisy IMF is calculated using t-test and founded that first four IMF contain the noise which can also be examined by the below IMF plot of several IMF .The first raw represent the clean ecg signal remaining are the IMF of the signal.

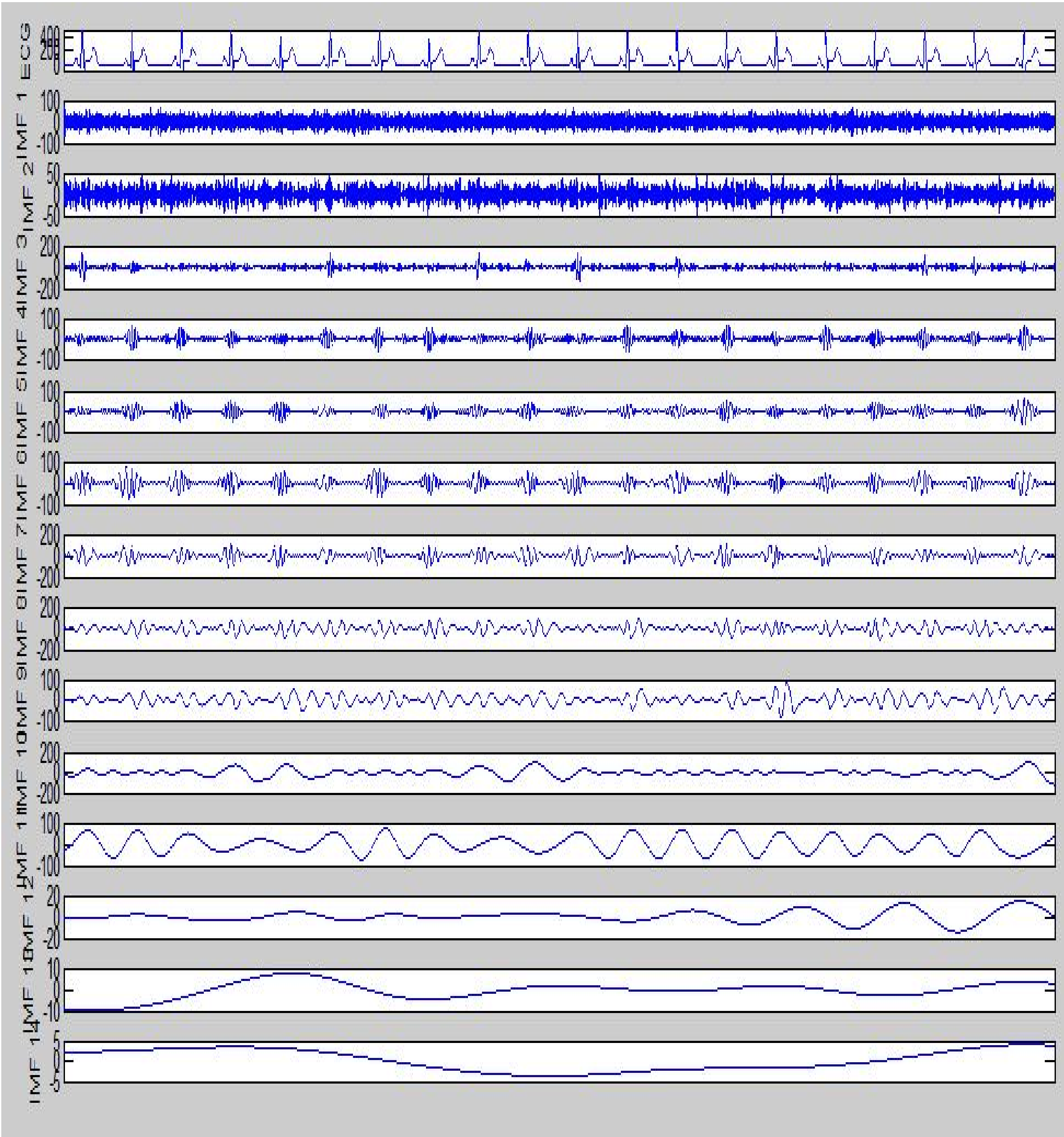


Fig:18 IMFs plot of the noisy signal including clean ecg signal (for ECG record 103)

From the above figure it is clearly observed that maximum noise present in the first four IMF. So the choice of selecting first four IMF is significant remaining IMF are insignificant.

4.2 Denoising for White Gaussian noise

The ECG signal is taken from the MIT-BIH arrhythmia database records & the synthetic addative white guassian noise noise is added to the signal for the examine the proposed algorithm. Then the noisy signal is applied to the EMD/EEMD which decompose the noisy signal in several IMF. As presented above in the figure18 only starting four imf is taken into consideration because maximum noise is presented in starting four IMF. All the algorithm are simulated in the matlab for analysis of the result and it is found that the constructed signal is very close to the original signal that is the noise free signal.

For the quantitative analysis the algorithm is performed on ECG signal records 103,213 from MIT BIH and on synthetic signal also AWGN noise is added to it. Given below table shows the results the same and clearly depicts that resulting SNR, MSE and Correlation Coefficient gives the better results than the existing algorithm.

Various methods are performed for the denoising of the ECG signal on various type of MIT-BIH arrhythmia database and also on synthetic Signal. Accordingly their parameter are calculated and results are compared.

In this thesis we use four various type of methods EED followed by moving average filter , EMD followed by median filter , EEMD followed by moving average filter and EEMD followed by median filter. Which are denoted as :

M 1 represents EMD followed by Moving average filter

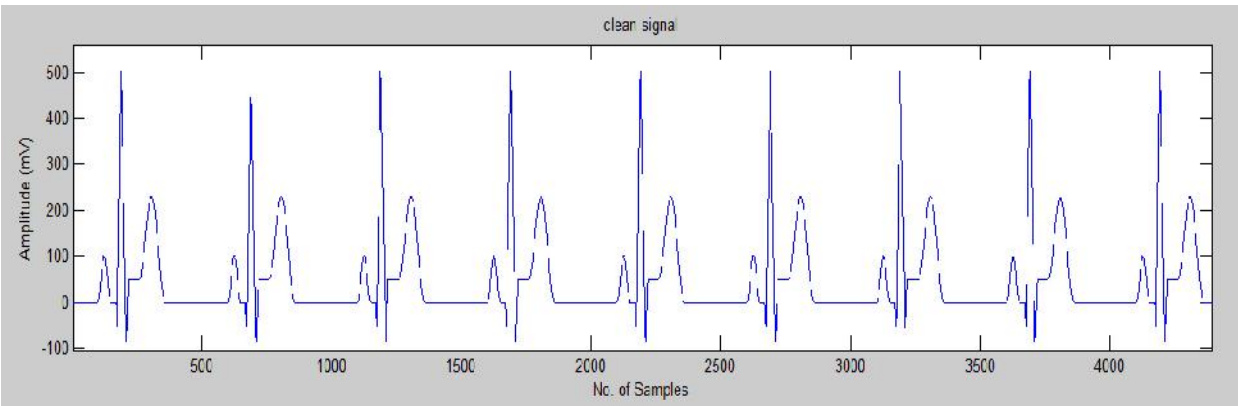
M 2 represents EMD followed by Median filter

M 3 represents EEMD followed by Moving average filter

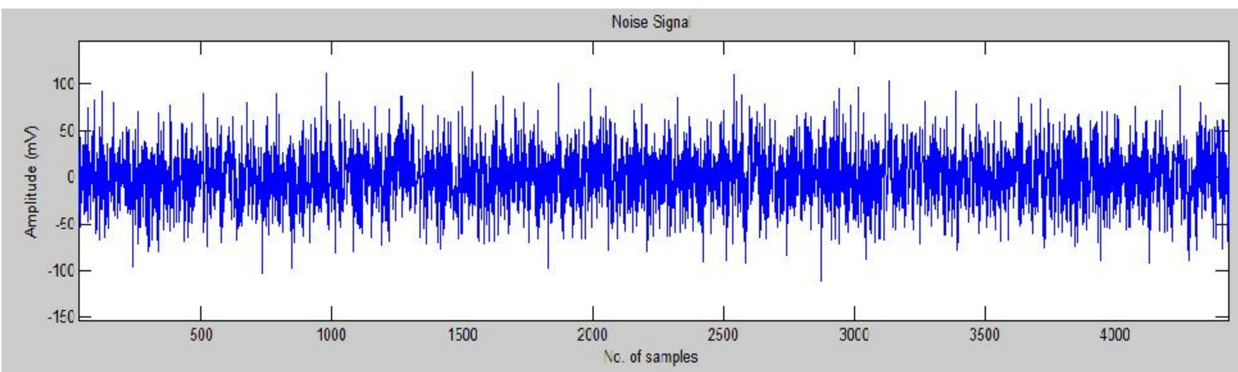
M 4 represents EEMD followed by Median filter

Results for ECG recording 103:

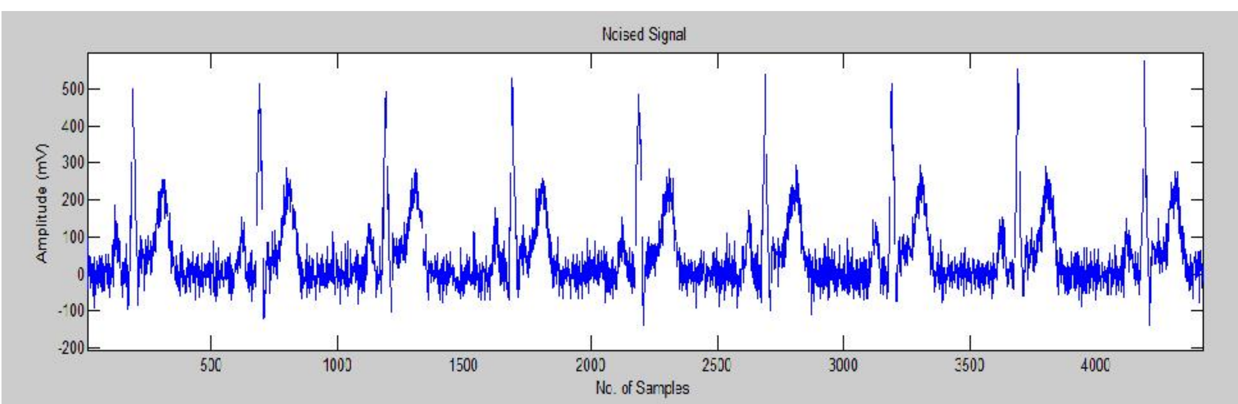
A) Time Domain Plot:



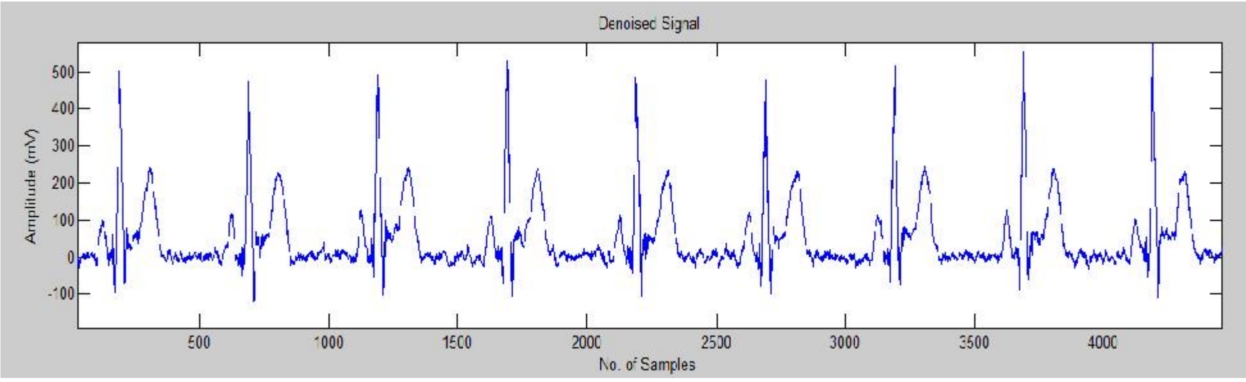
a) Clean signal



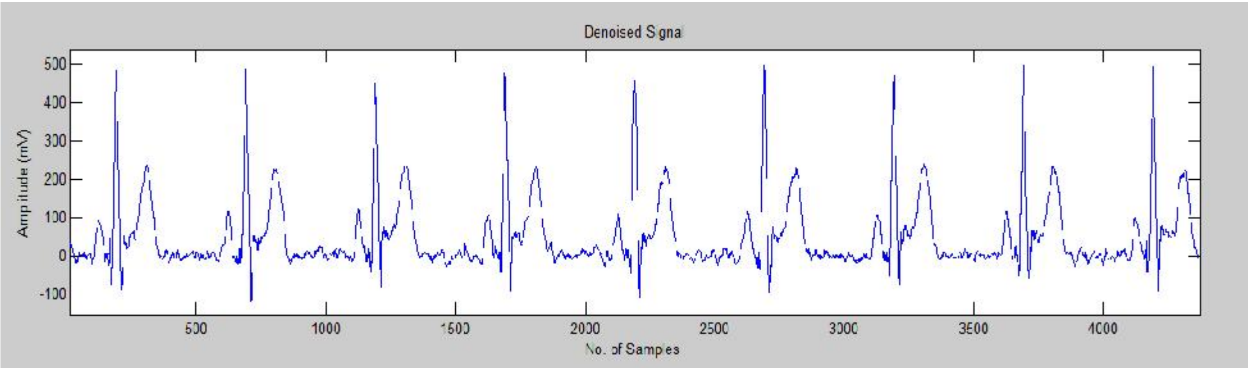
b) Noise signal



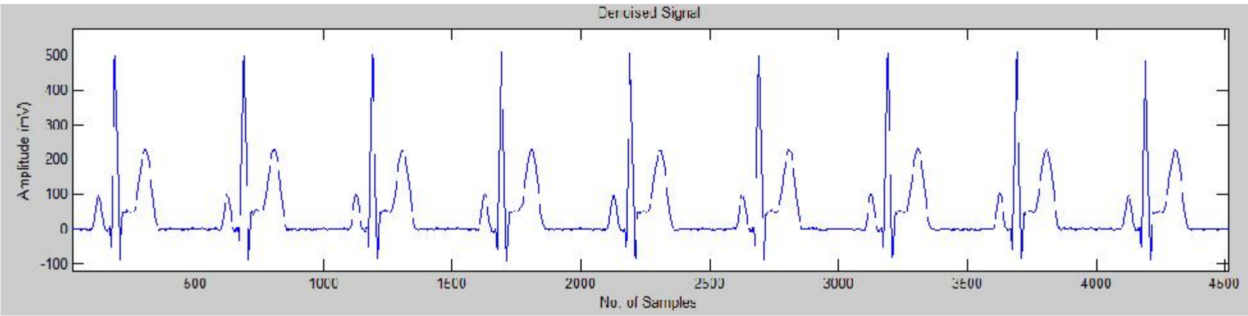
c) Noised signal



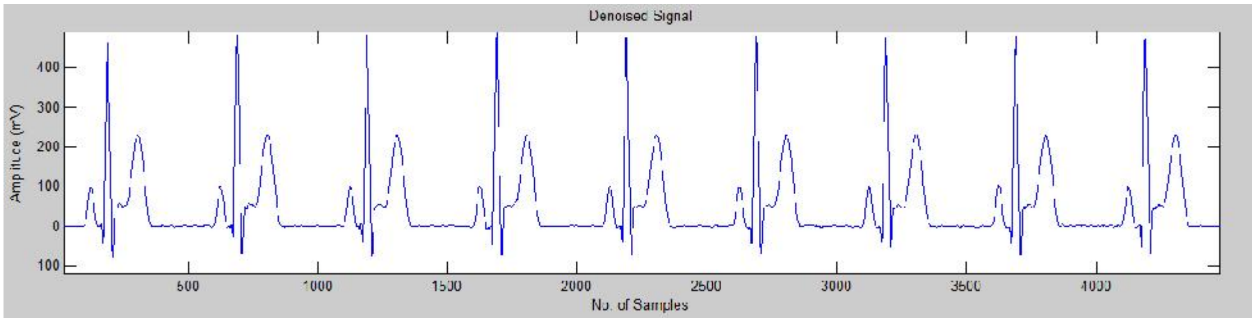
d) Denoised Signal by Method M1



e) Denoised Signal by Method M2



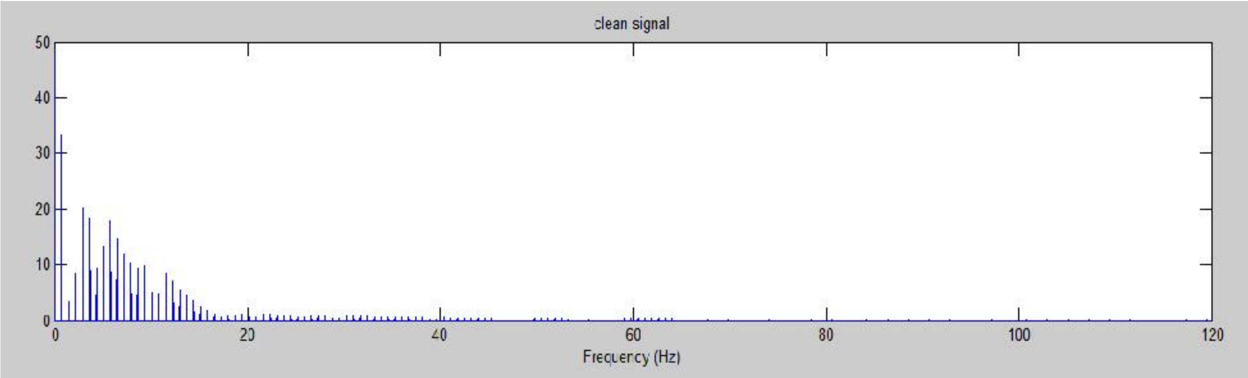
f)Denoised Signal by Method M3



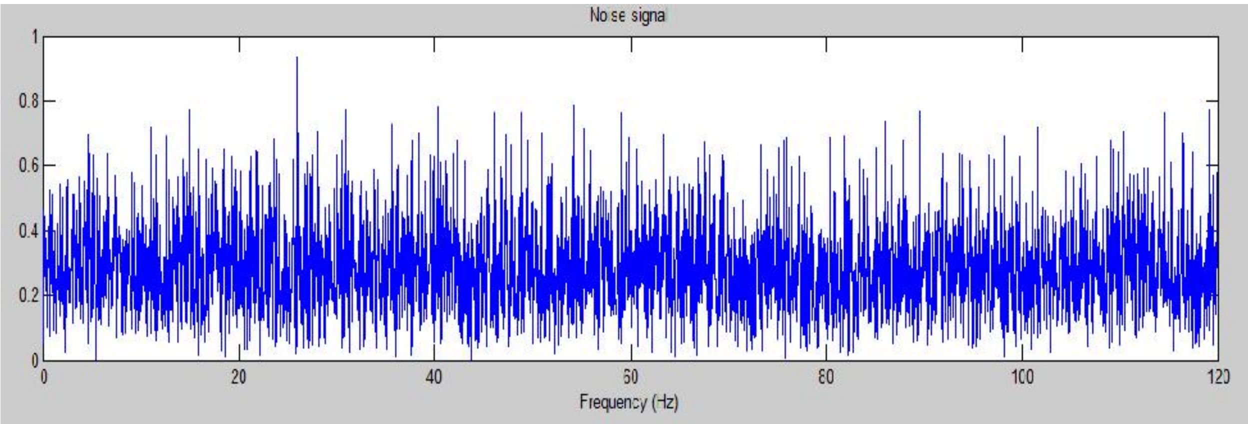
g)Denoised Signal by Method M4

Fig : 19 Time domain a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

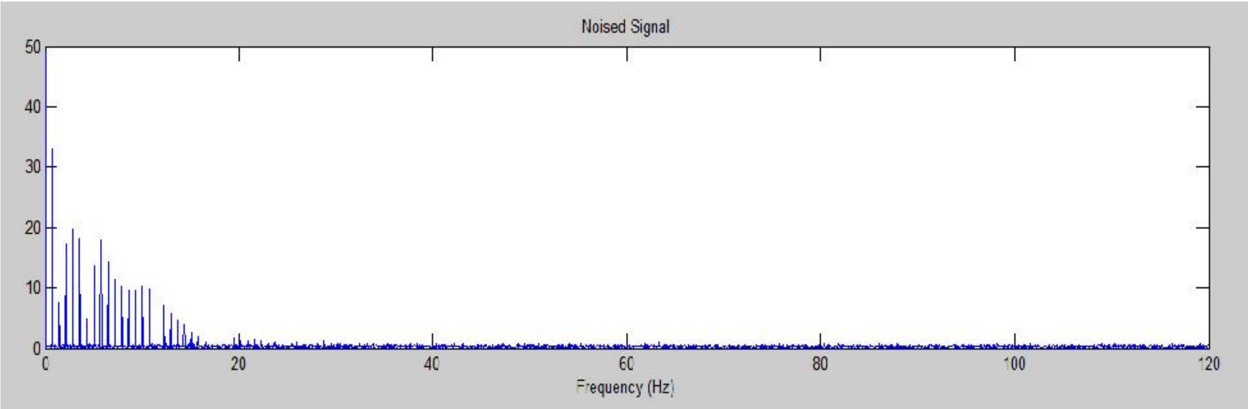
B) Frequency Domain Plot:



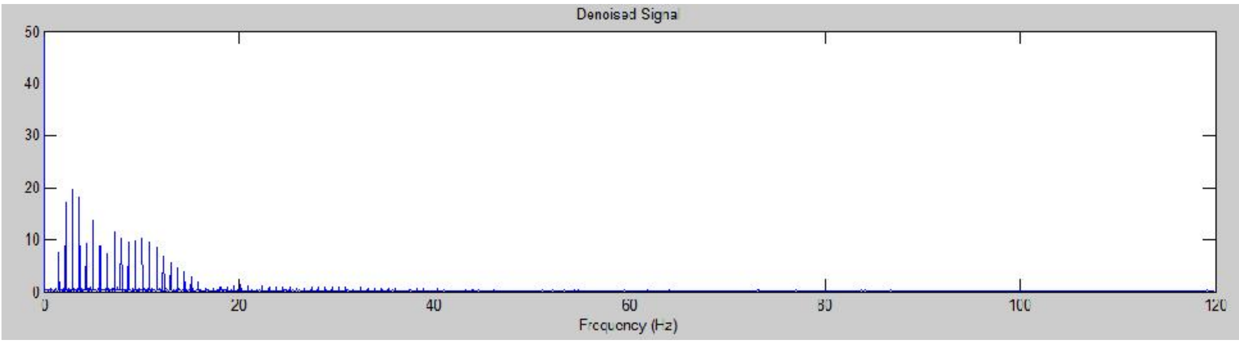
a) Clean signal



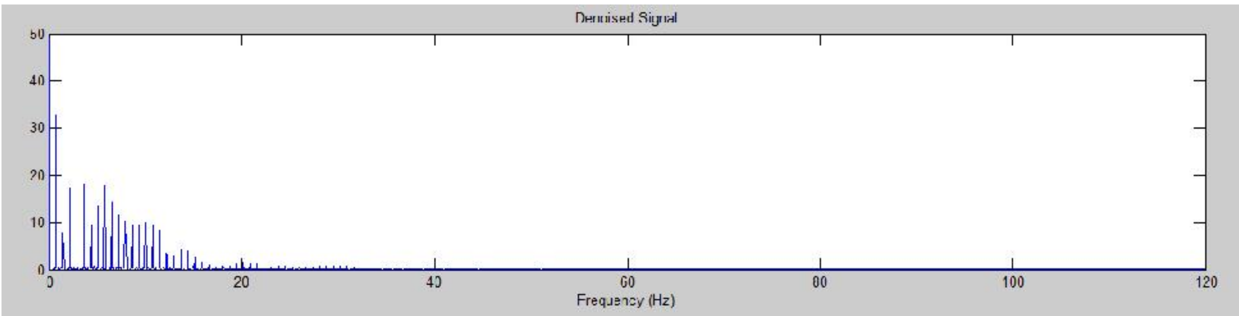
b) Noise signal



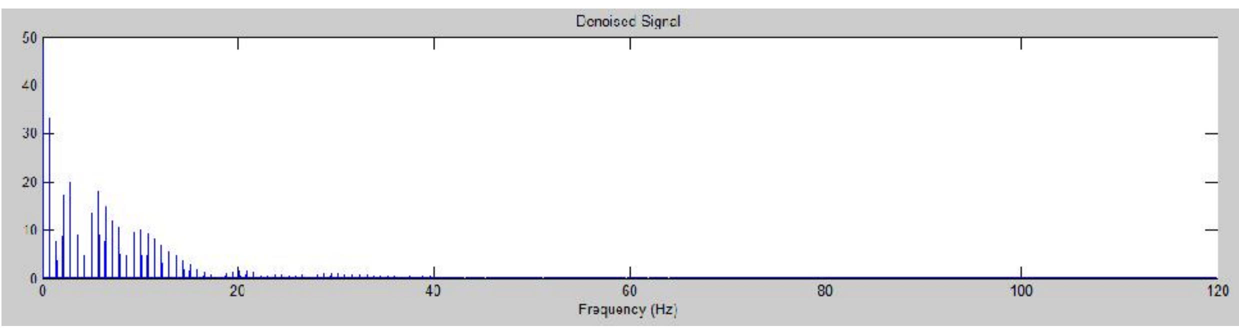
c) Noised Signal



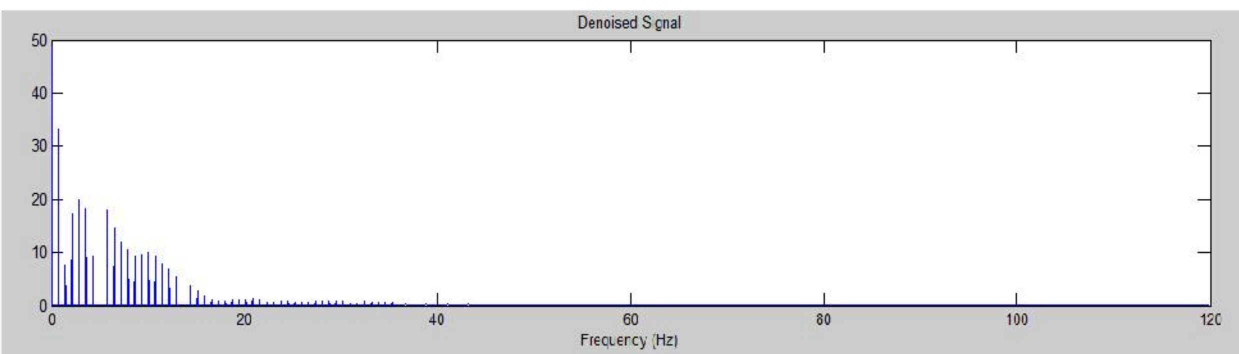
a) Denoised signal by method M1



b) Denoised signal by method M2



c) Denoised signal by method M3



d) Denoised signal by method M4

Fig : 20 Frequency domain of a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

C) Table for SNR, MSE and Correlation Coefficient

i) Output SNR (for input SNR = 23.1980 dB)

Method	Output SNR (dB)
M1 (EMD + Moving Avg. Filter)	38.4823
M2 (EMD + Median Filter)	41.5090
M3 (EEMD + Moving Avg. Filter)	74.7328
M4 (EEMD + Median Filter)	72.3018

ii) Output MSE (for input MSE = 994.0939)

Method	Output MSE
M1 (EMD + Moving Avg. Filter)	215.5952
M2 (EMD + Median Filter)	159.2902
M3 (EEMD + Moving Avg. Filter)	5.7451
M4 (EEMD + Median Filter)	7.3262

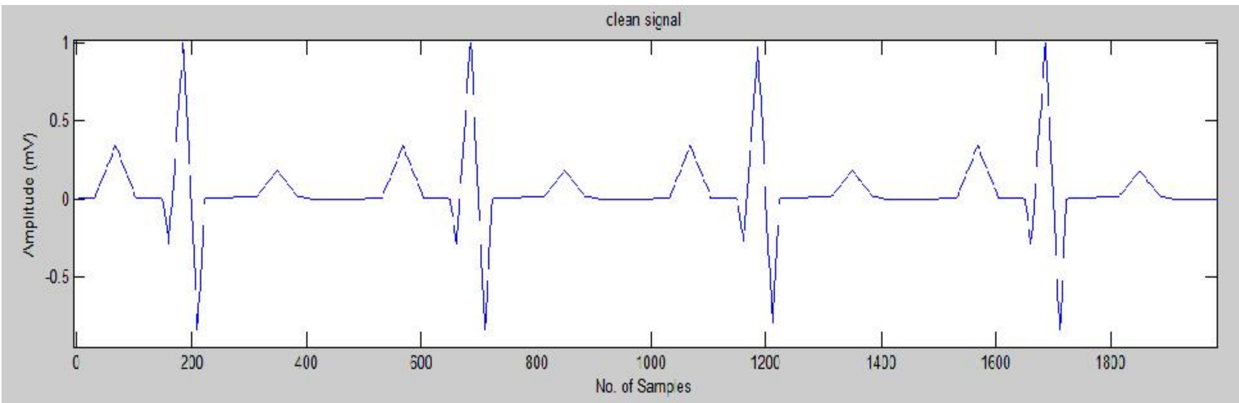
iii) Correlation Coefficient

Method	Correlation Coefficient
M1 (EMD + Moving Avg. Filter)	0.9931
M2 (EMD + Median Filter)	0.9948
M3 (EEMD + Moving Avg. Filter)	0.9998
M4 (EEMD + Median Filter)	0.9998

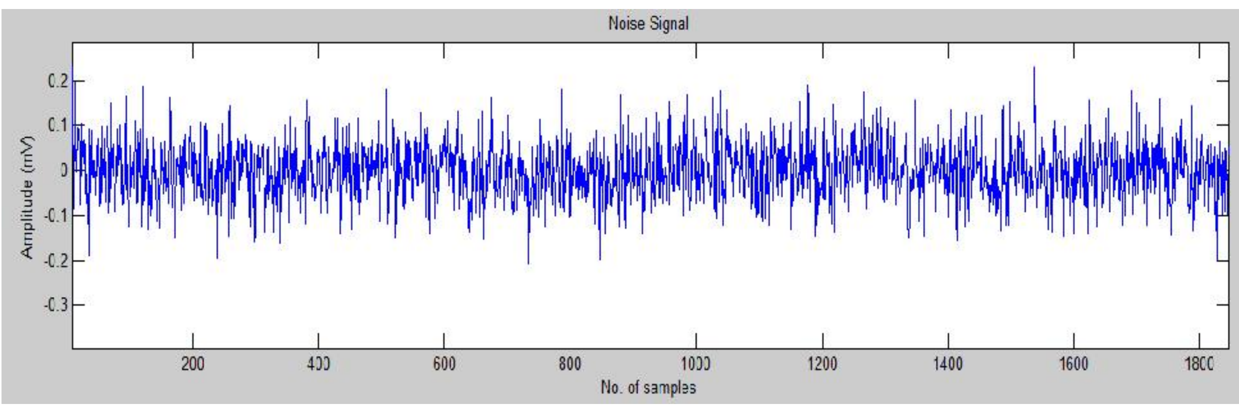
Table 1 : SNR, MSE and Correlation coefficient of ECG signal 103

Results for Synthetic Signal

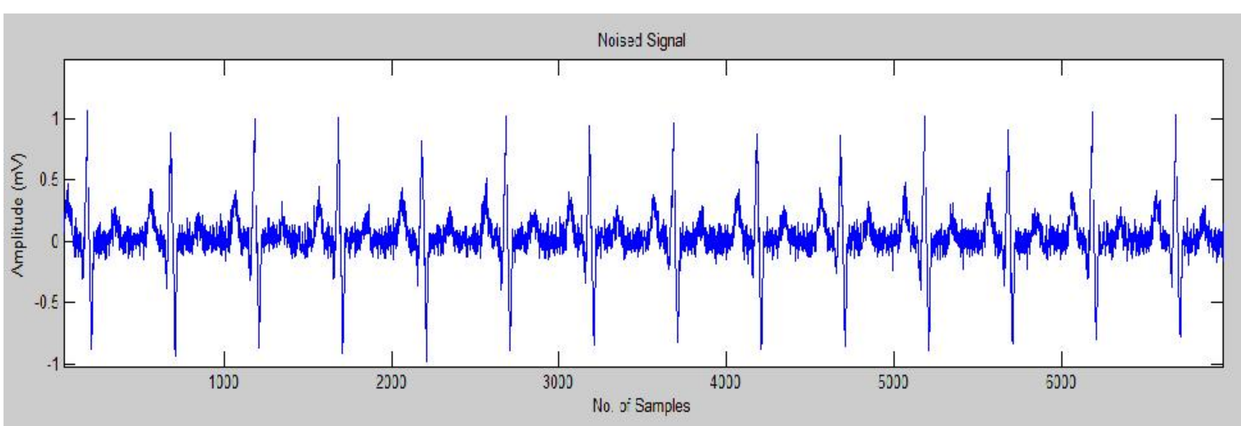
A) Time Domain Plot



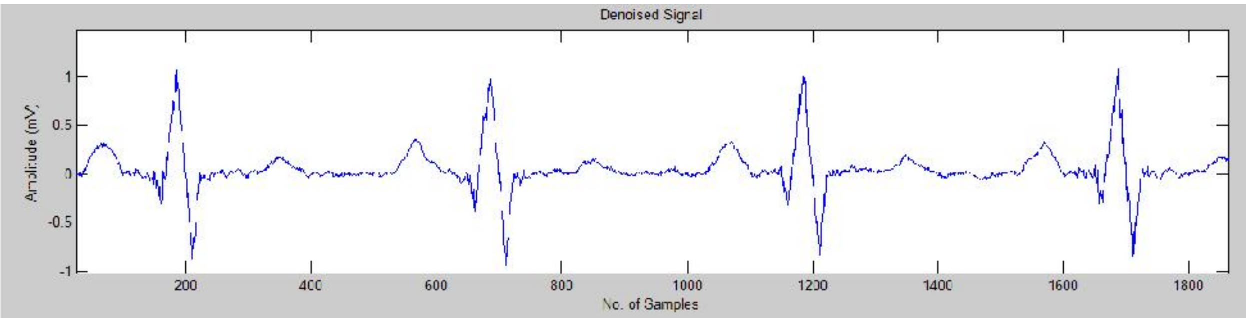
a) Clean signal



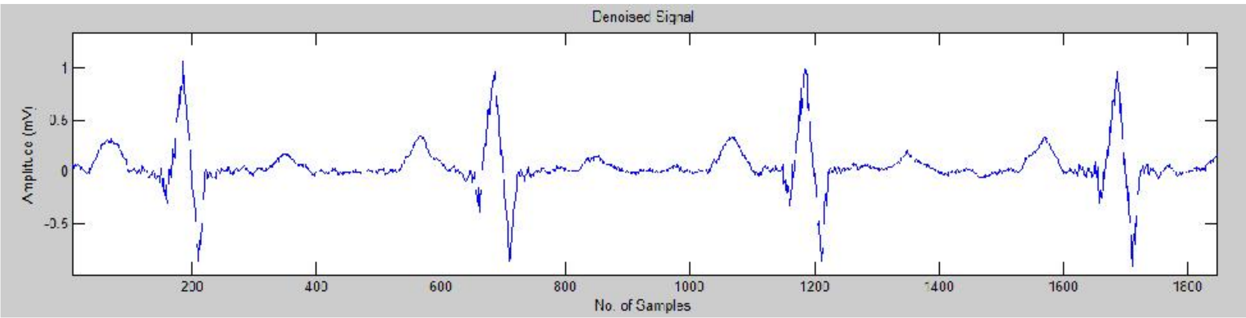
b) Noise signal



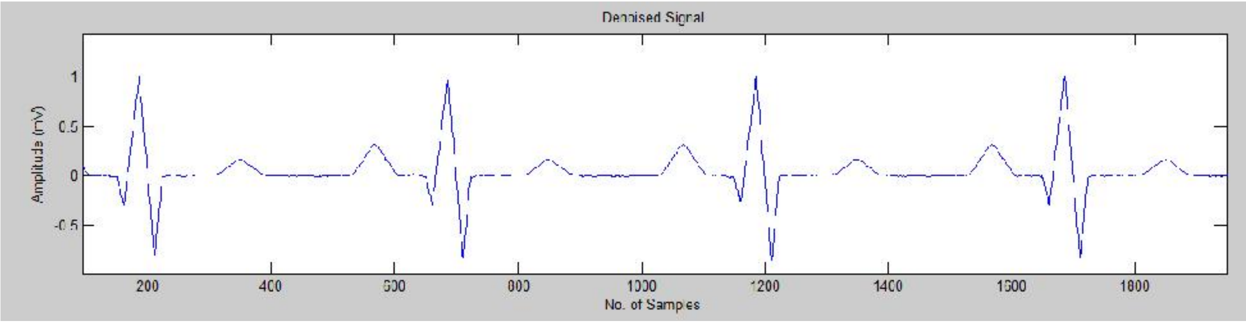
c) Noised signal



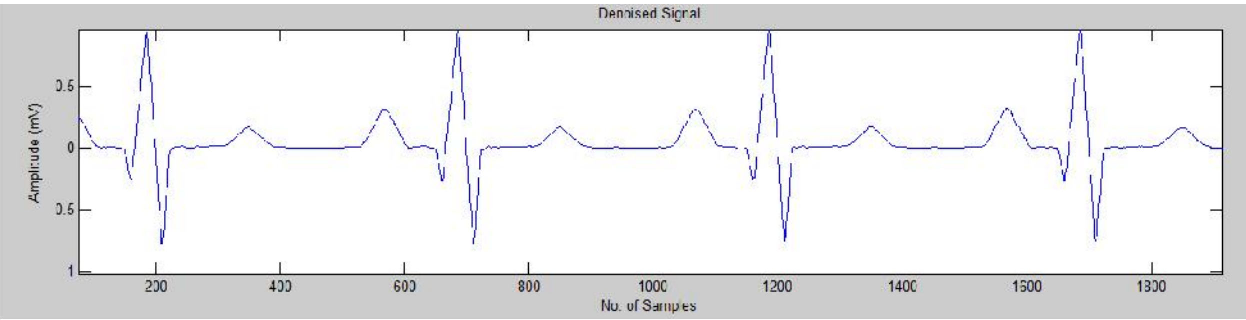
d) Denoised signal by method M1



e) Denoised signal by method M2



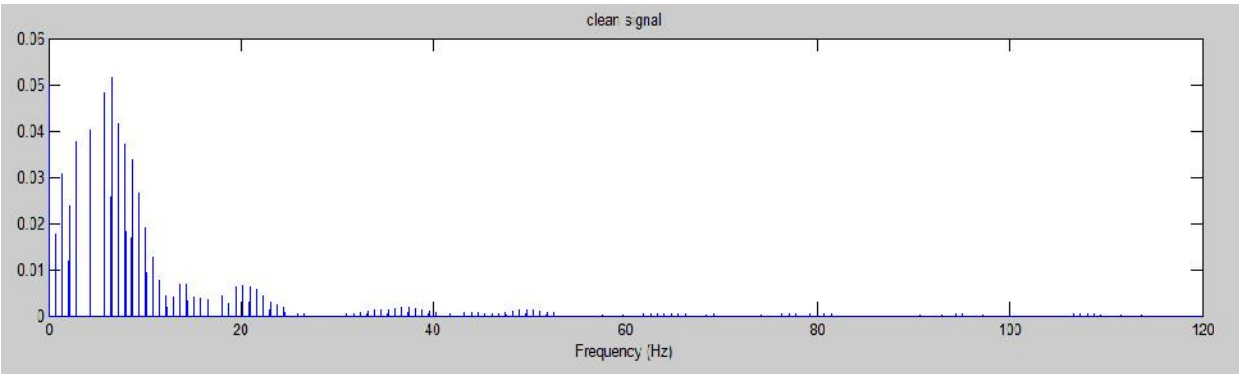
f) Denoised signal by method M3



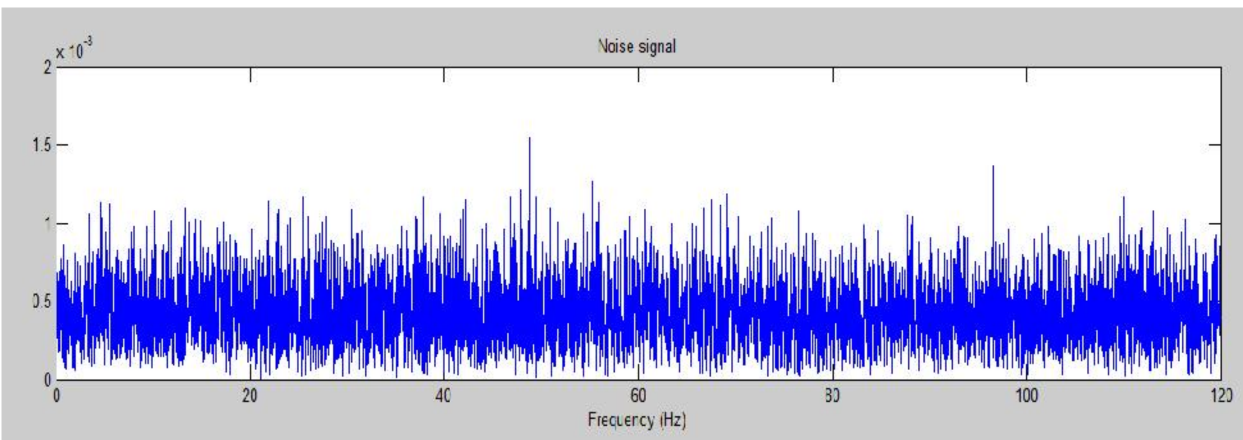
g) Denoised signal by method M4

Fig : 21 Time domain a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

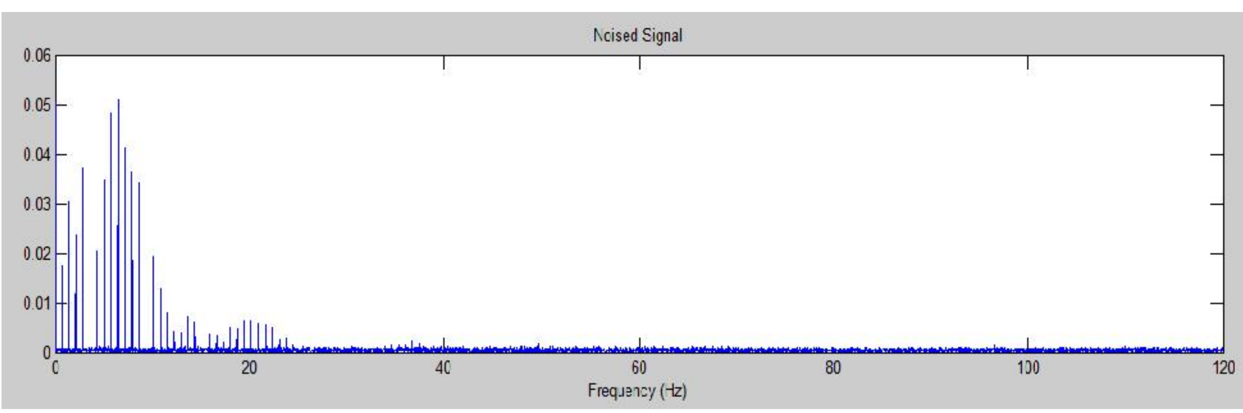
B) Frequency Domain plot:



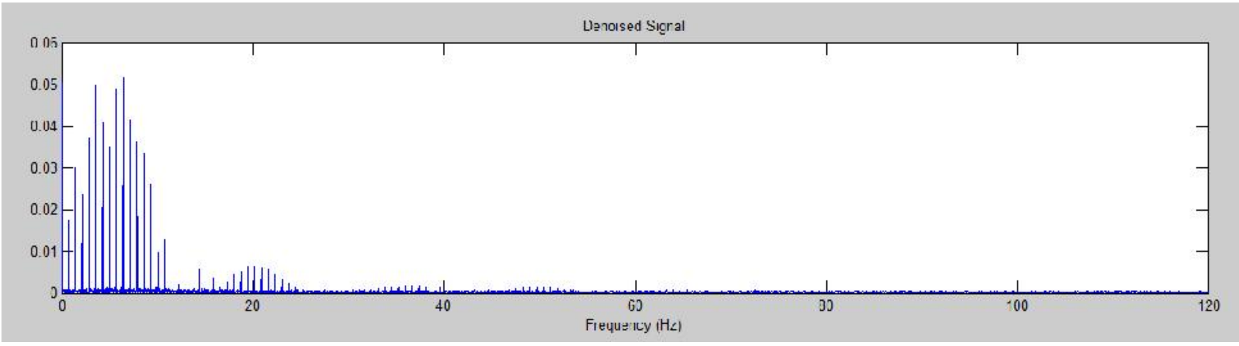
a) clean signal



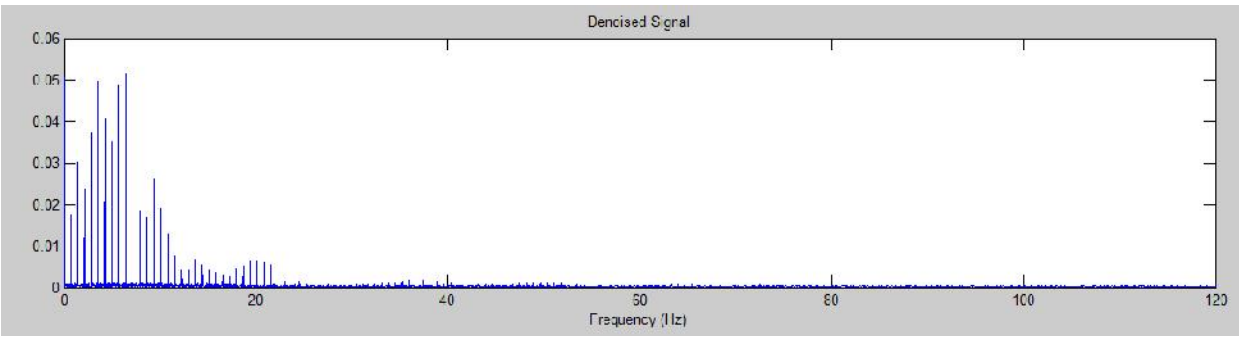
b) Noise signal



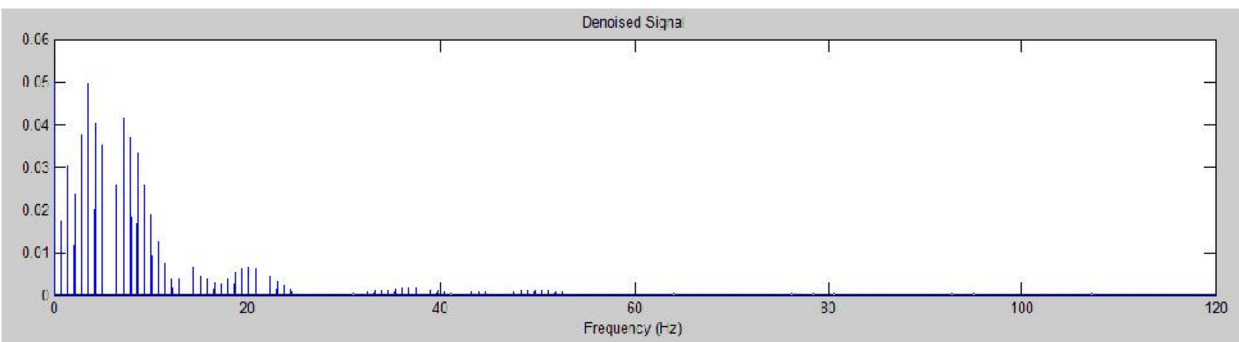
c) Noised signal



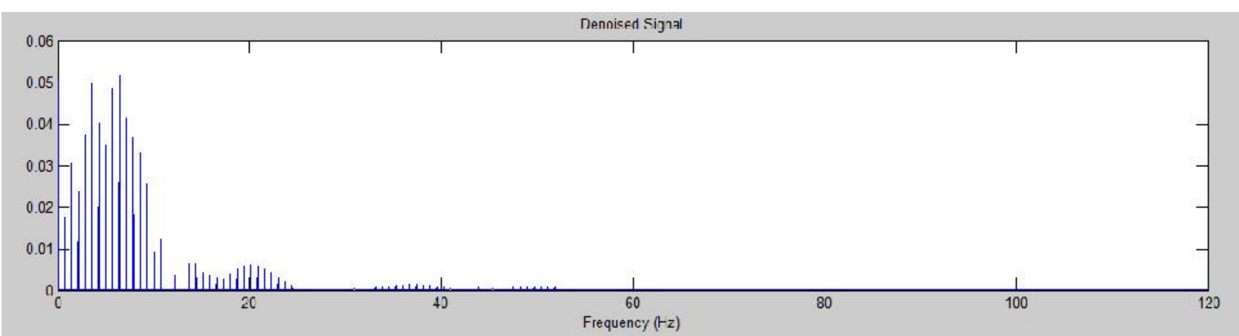
d) Denoised signal by method M1



e) Denoised signal by method M2



f) Denoised signal by method M3



g) Denoised signal by method M4

Fig : 22 Frequency domain of a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

C) Table for SNR, MSE and Correlation Coefficient

i) Output SNR (for input SNR =23.2401)

Method	Output SNR
M1 (EMD + Moving Avg. Filter)	36.6397
M2 (EMD + Median Filter)	39.9713
M3 (EEMD + Moving Avg. Filter)	72.0931
M4 (EEMD + Median Filter)	68.2799

ii) Output MSE (for input MSE =0.0040)

Method	Output MSE
M1 (EMD + Moving Avg. Filter)	0.0011
M2 (EMD + Median Filter)	0.00076415
M3 (EEMD + Moving Avg. Filter)	0.0000305
M4 (EEMD + Median Filter)	0.0000447

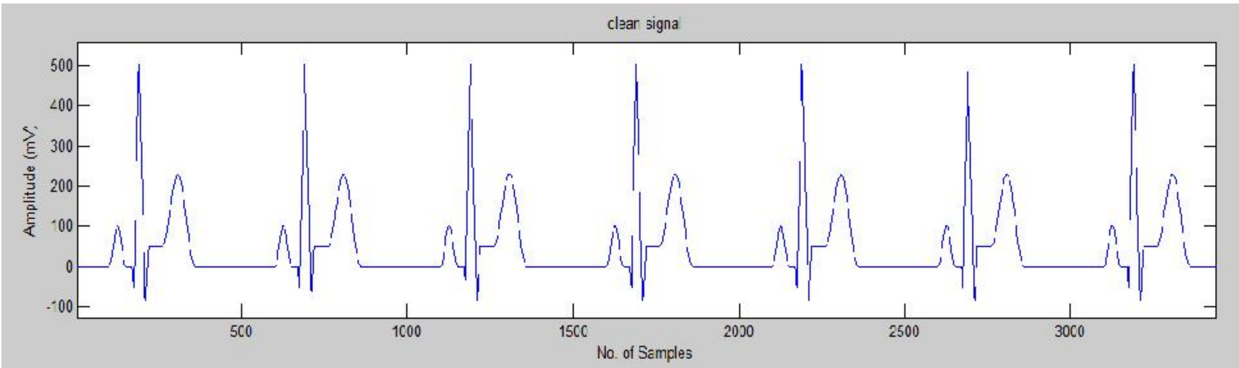
iii) Correlation Coefficient

Method	Correlation Coefficient
M1 (EMD + Moving Avg. Filter)	0.9933
M2 (EMD + Median Filter)	0.9951
M3 (EEMD + Moving Avg. Filter)	0.9998
M4 (EEMD + Median Filter)	0.9997

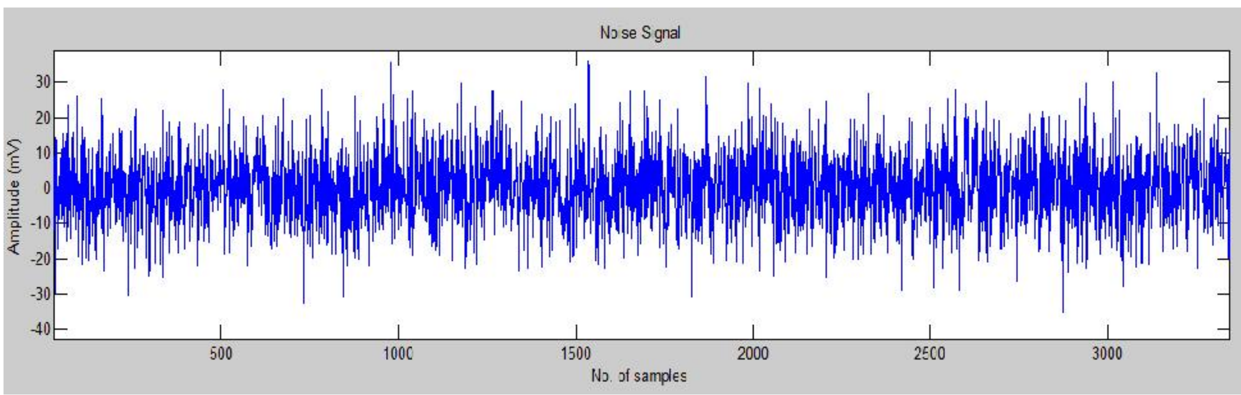
Table 2 : SNR, MSE and Correlation coefficient of ECG Synthetic signal

Results for ECG recoding 213 MIT-BIH :

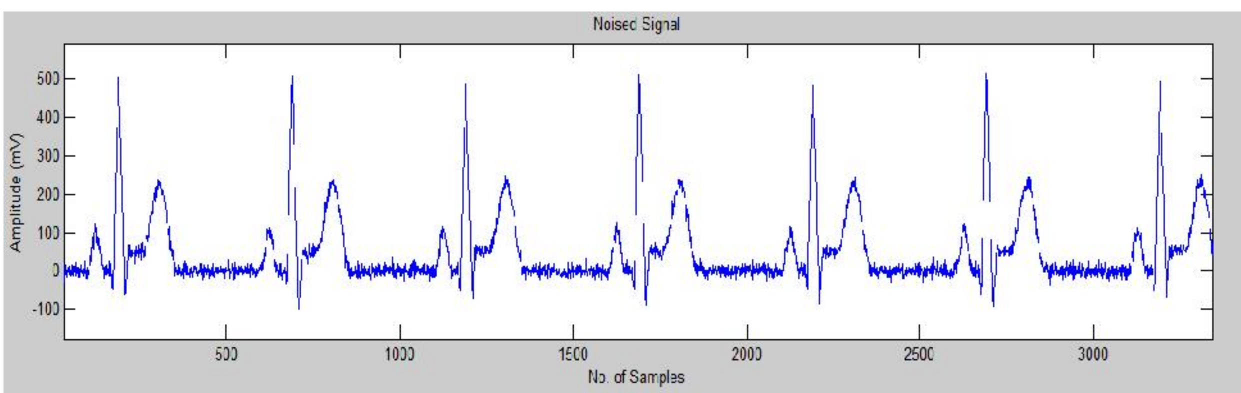
A) Time Domain Plot



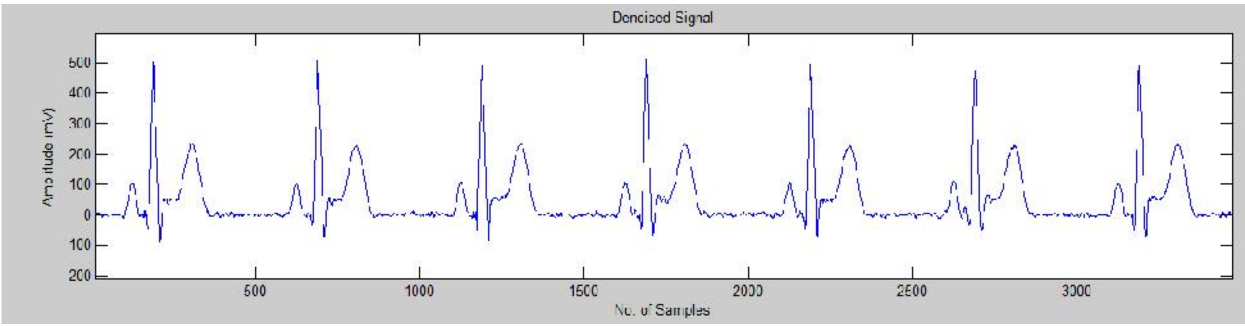
a) Clean signal



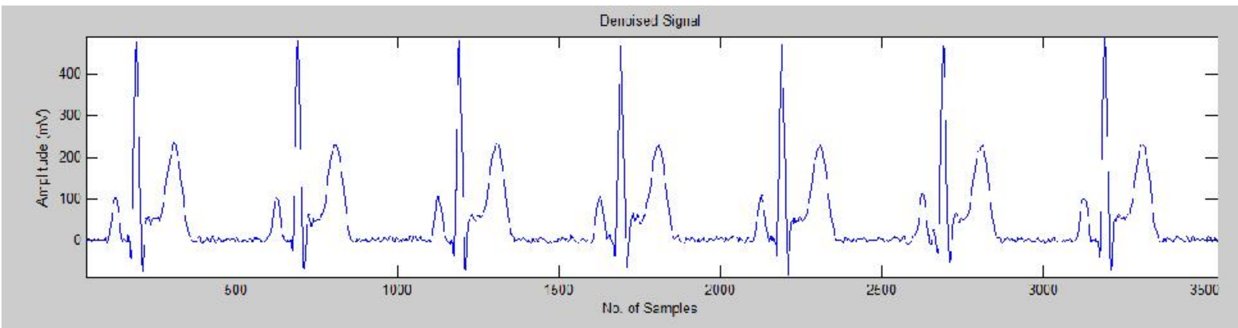
b) Noise signal



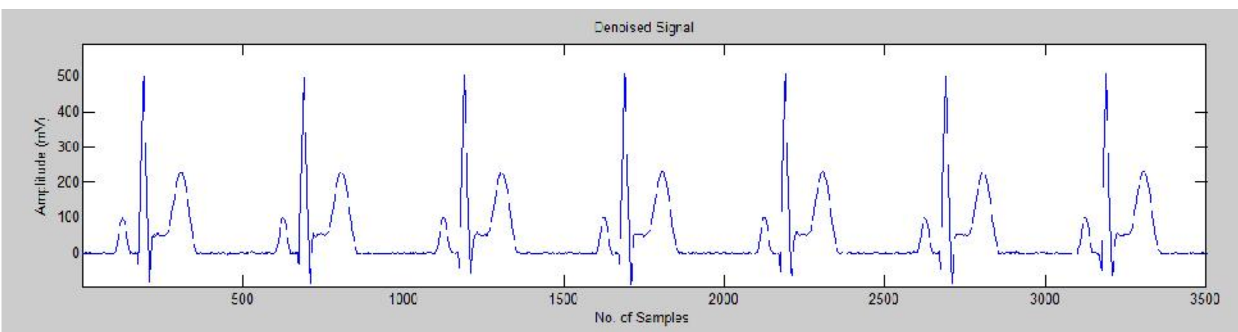
c) Noised signal



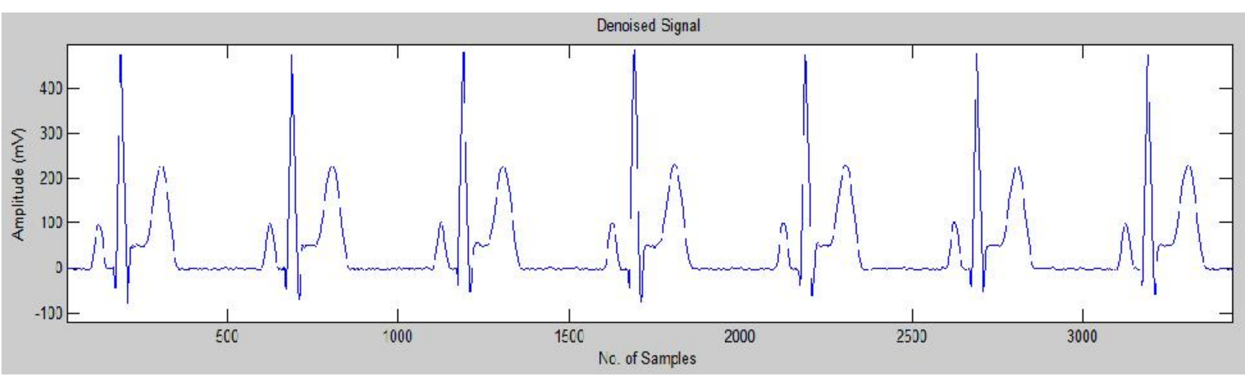
d) Denoised signal by method M1



e) Denoised signal by method M2



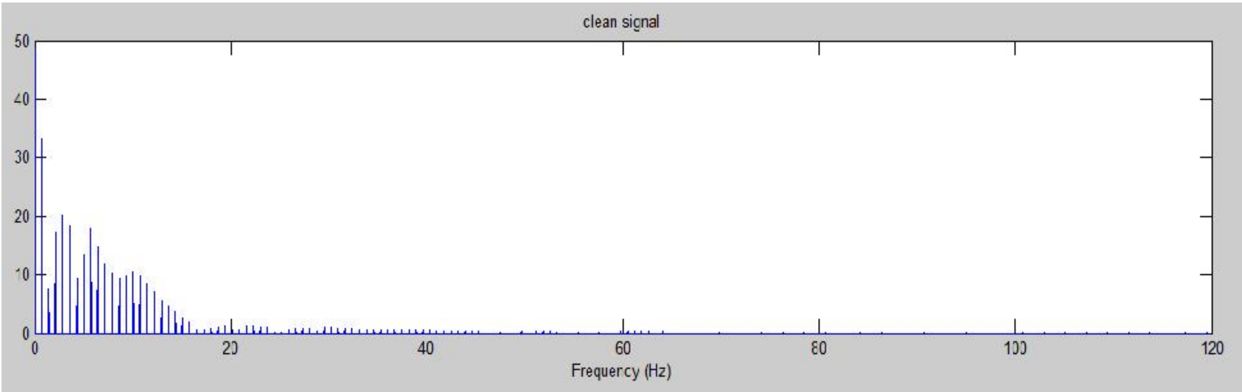
f) Denoised signal by method M3



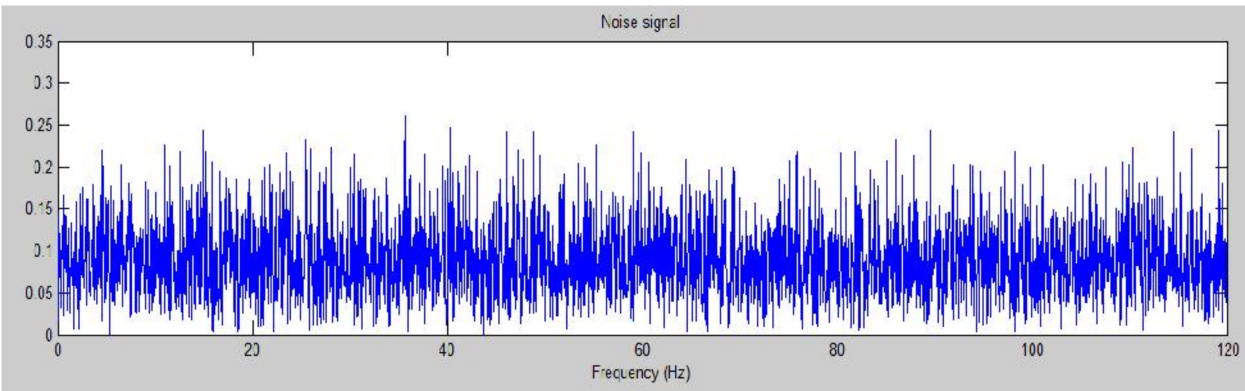
g) Denoised signal by method M4

Fig : 23 Time domain of a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

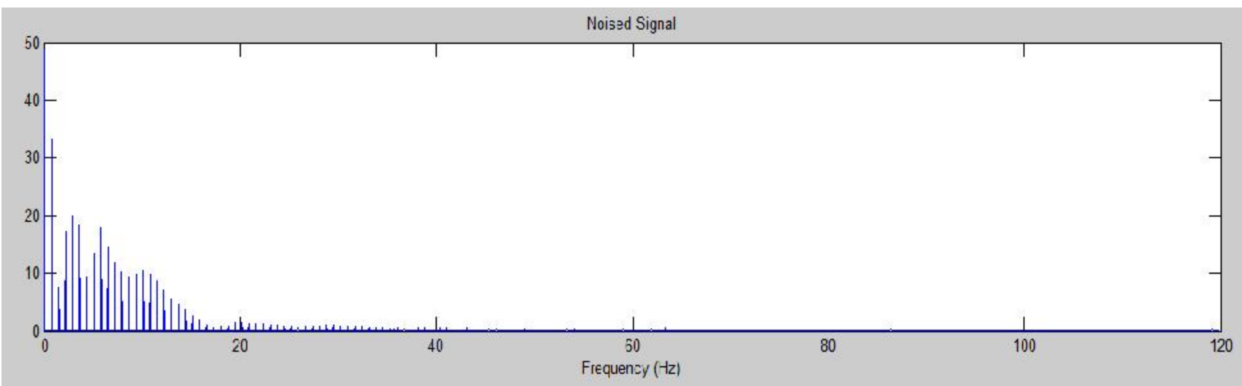
B) Frequency domain Plot:



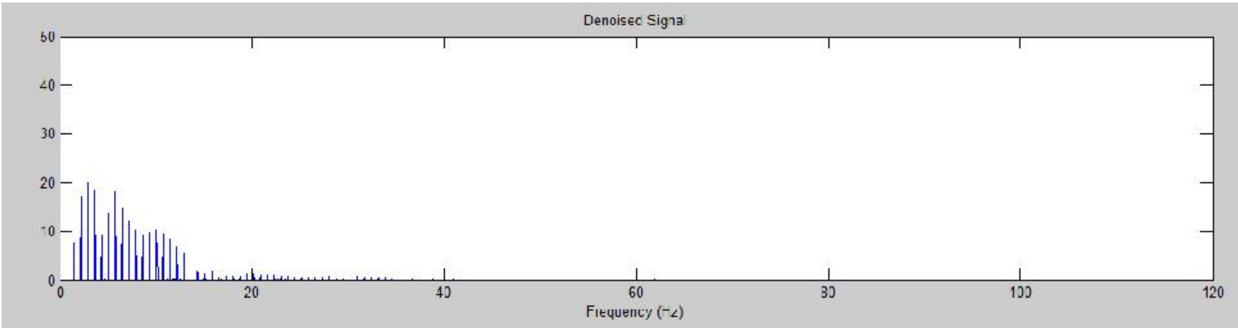
a) Clean signal



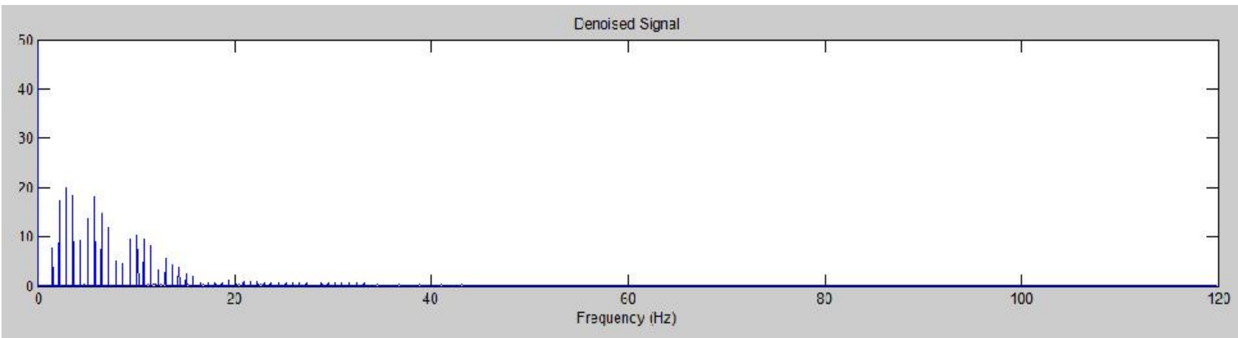
b) Noise signal



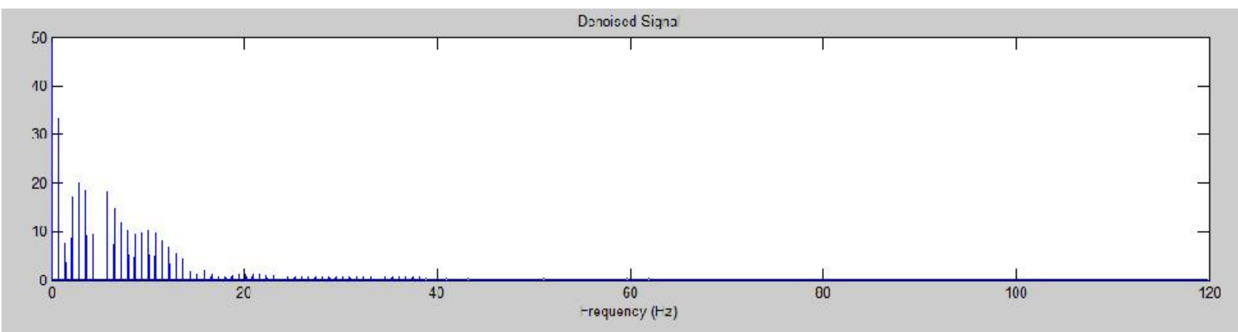
c) Noised signal



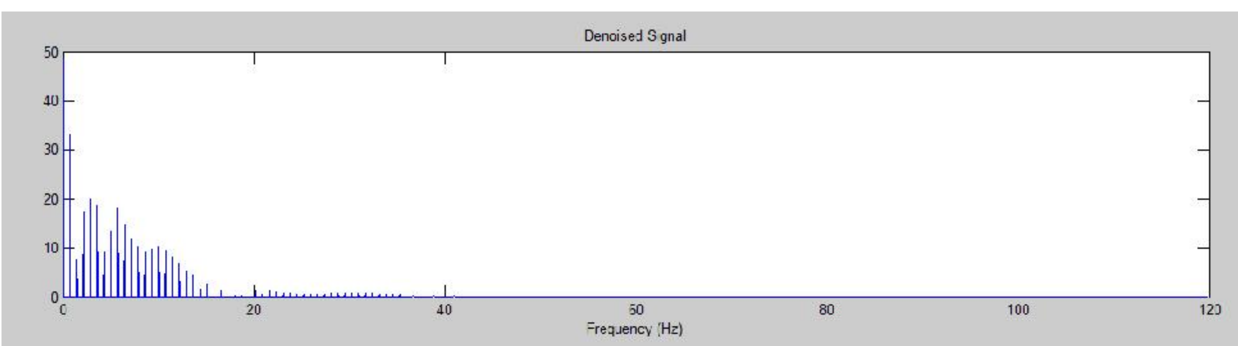
d) Denoised signal by method M1



e) Denoised signal by method M2



f) Denoised signal by method M3



g) Denoised signal by method M4

Fig : 24 Frequency domain of a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

C) Table for SNR, MSE and Correlation Coefficient

i) Output SNR (for input SNR=46.2239)

Method	Output SNR
M1 (EMD + Moving Avg. Filter)	56.2613
M2 (EMD + Median Filter)	56.4001
M3 (EEMD + Moving Avg. Filter)	73.2690
M4 (EEMD + Median Filter)	71.1074

ii) Output MSE(for input MSE=99.4094)

Method	Output MSE
M1 (EMD + Moving Avg. Filter)	36.4339
M2 (EMD + Median Filter)	35.9319
M3 (EEMD + Moving Avg. Filter)	6.6542
M4 (EEMD + Median Filter)	8.2556

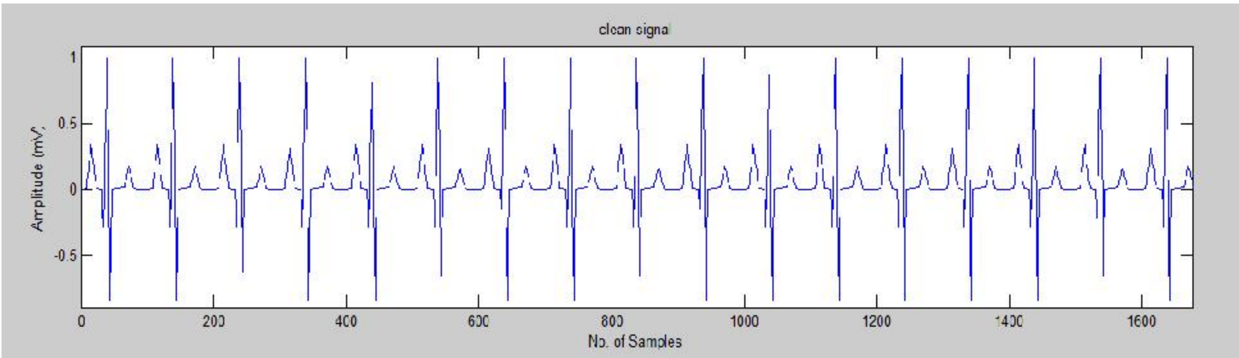
iii) Correlation Coefficient

Method	Correlation Coefficient
M1 (EMD + Moving Avg. Filter)	0.9988
M2 (EMD + Median Filter)	0.9988
M3 (EEMD + Moving Avg. Filter)	0.9998
M4 (EEMD + Median Filter)	0.9997

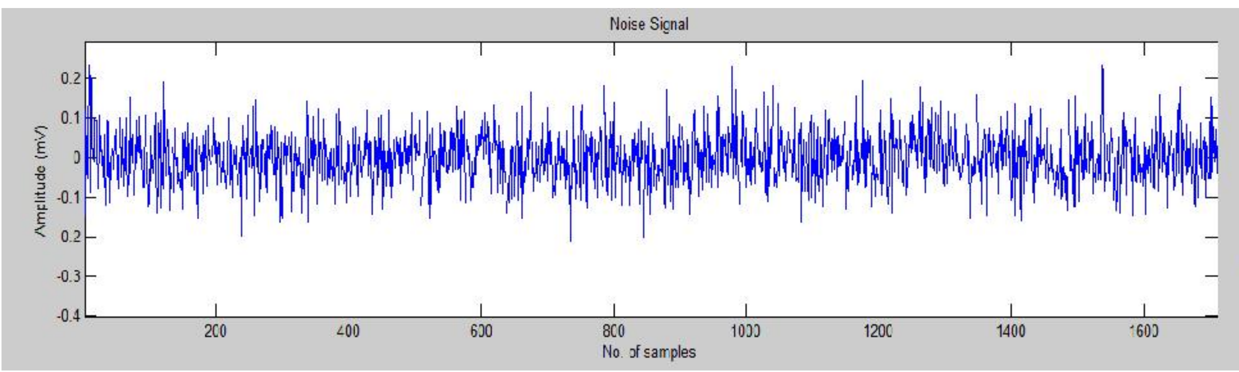
Table 3 : SNR, MSE and Correlation coefficient of ECG signal 213.

Results for ECG Synthetic record 2:

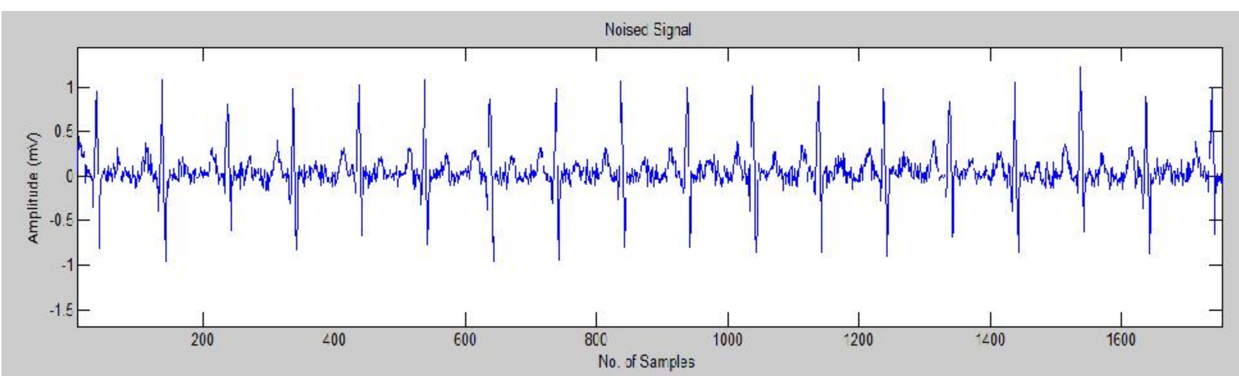
A) Time domain plot:



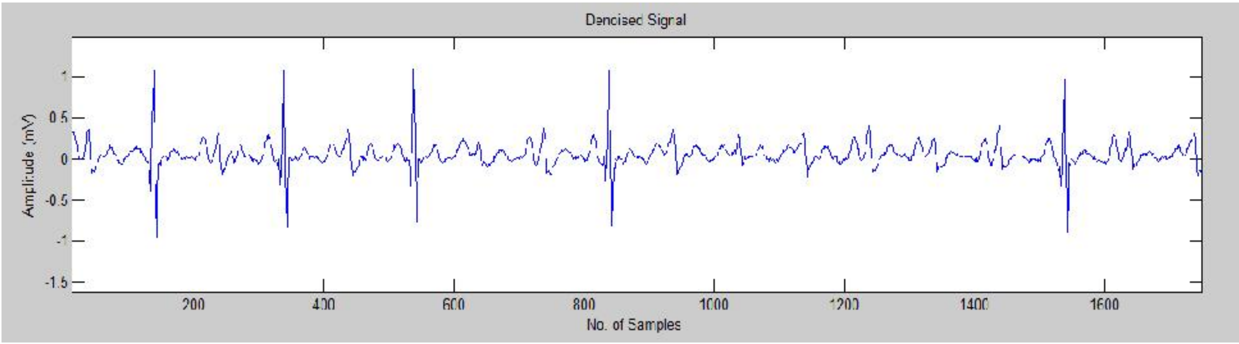
a) Clean signal



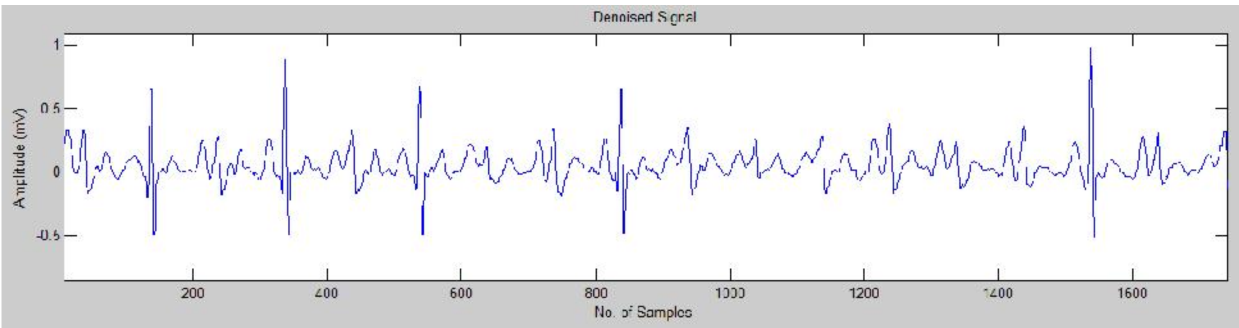
b) Noise signal



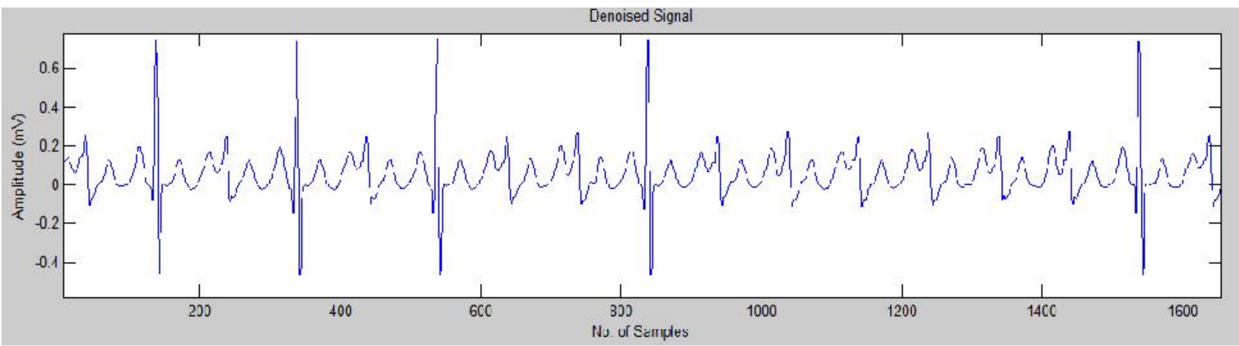
c) Noised signal



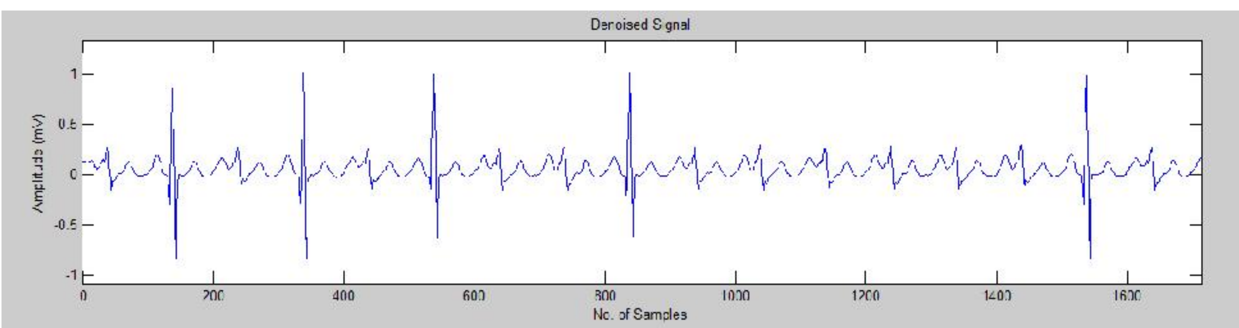
d) Denoised signal by method M1



e) Denoised signal by method M2



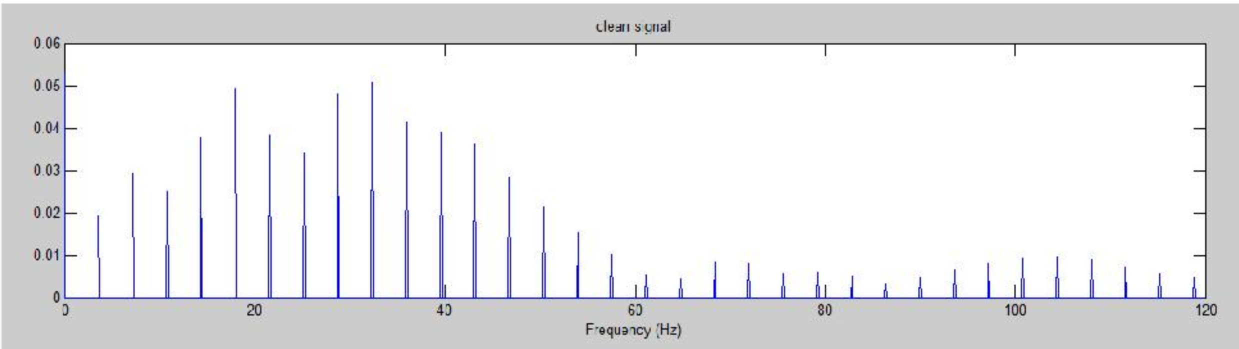
f) Denoised signal by method M3



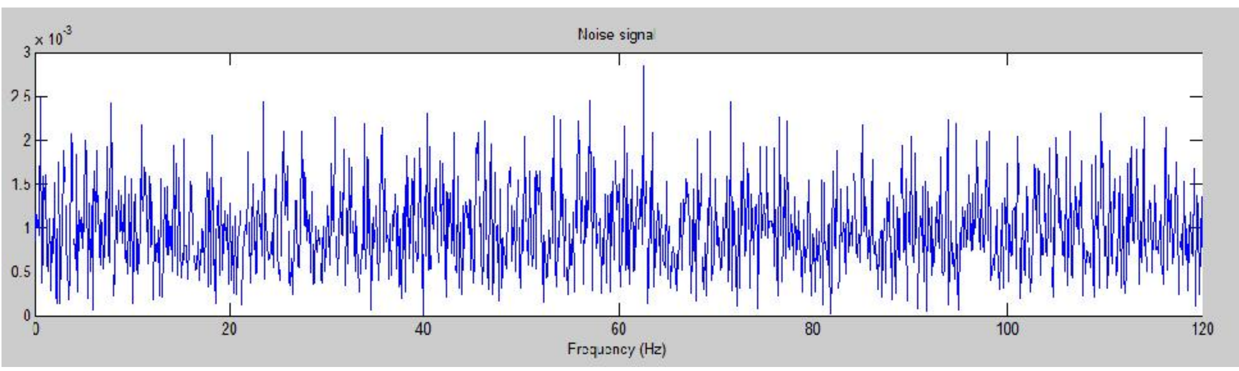
g) Denoised signal by method M4

Fig : 25 Time domain a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

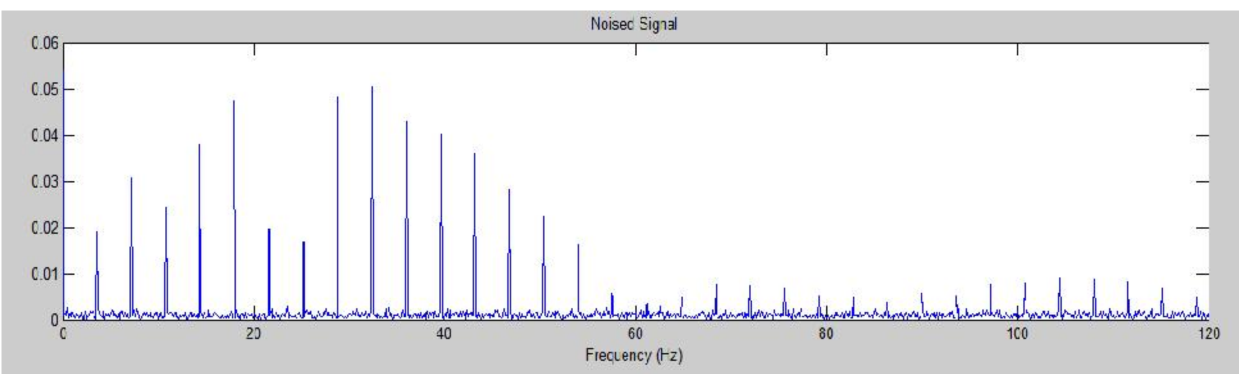
B) Frequency Domain Plot:



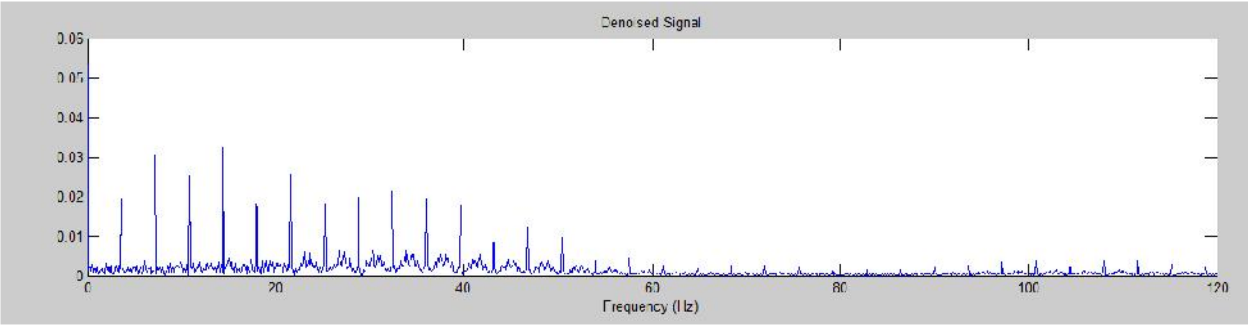
a) Clean signal



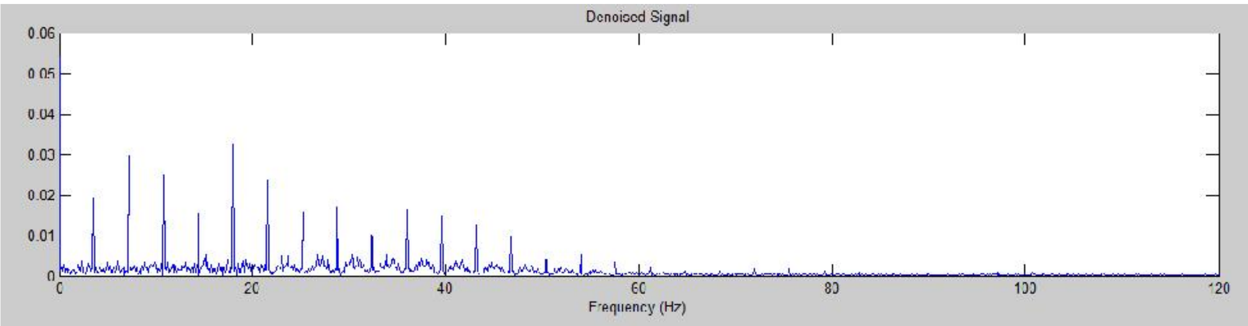
b) Noise signal



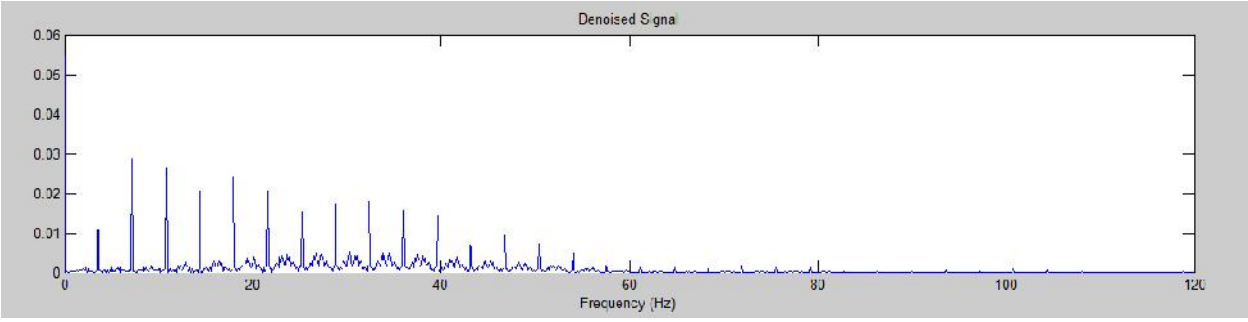
c) Noised signal



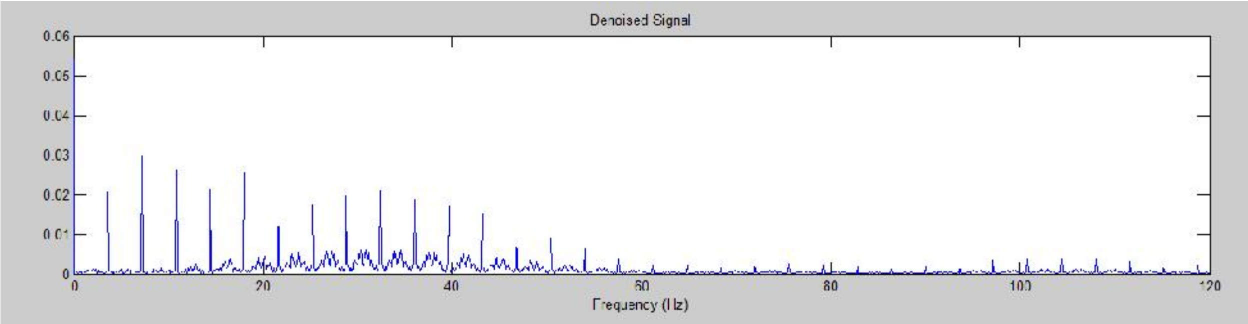
d) Denoised signal by method M1



e) Denoised signal by method M2



f) Denoised signal by method M3



g) Denoised signal by method M4

Fig : 26 Frequency domain of a)clean signal b)noise signal c)noised signal d)denoised signal by method M1 e)denoised signal by method M2 f)denoised signal by method M3 g)denoised signal by method M4

C) Table for SNR, MSE and Correlation Coefficient

i) Output SNR (for input SNR= 23.1980)

Method	Output SNR
M1 (EMD + Moving Avg. Filter)	10.2073
M2 (EMD + Median Filter)	9.5224
M3 (EEMD + Moving Avg. Filter)	9.1122
M4 (EEMD + Median Filter)	9.9646

ii) Output MSE(for input MSE= 0.0042)

Method	Output MSE
M1 (EMD + Moving Avg. Filter)	0.01564
M2 (EMD + Median Filter)	0.0165
M3 (EEMD + Moving Avg. Filter)	0.0172
M4 (EEMD + Median Filter)	0.0158

iii) Correlation Coefficient

Method	Correlation Coefficient
M1 (EMD + Moving Avg. Filter)	0.8931
M2 (EMD + Median Filter)	0.8883
M3 (EEMD + Moving Avg. Filter)	0.9113
M4 (EEMD + Median Filter)	0.9112

Table 1 : SNR, MSE and Correlation coefficient of ECG synthetic signal 2.

CHAPTER FIVE

CONCLUSION & FUTURE WORK

5.1 Conclusion

“The technique explicated in this work deliberates that on applying empirical mode decomposition to the noisy ECG signal, IMFs include both, the content of the signal as well as noise components, thus only preservation of the useful content of the signal i.e the actual ECG signal is being considered as the main aim. The proposed method is melioration towards the existing EMD/EEMD based denoising approaches.”

This “approach of denoising includes the adaptive window technique followed by the smoothing of the preserved QRS complex within the specified QRS duration so that the reconstructed signal achieved is very much similar to the actual ECG signal. The qualitative as well as quantitative results obtained for various experiments show that the proposed algorithm is very much efficacious and promising one for the denoising of the ECG signal without changing the actual feature of the signal.”

Here an additional smoothing approach has been introduced to the QRS complex preserved after applying window function. It removes the additional peaks, due to which the actual feature of the QRS complex was deformed caused due to noises. The combination of the modified EMD approach and smoothing makes the algorithm very much realistic and applicable and can be applied in long term examination of the ECG signal in practical stress test as well as in Holter monitoring that may get affected by the prominent noises.

5.2 Future Work

Various algorithmic improvements about EMD/EEMD is proposed and need to be validated. EMD/EEMD is a powerful technique for analysing a signal thus it can be combined with other methods such as wavelet tranform, ICA and PCA based methods to enhance its capbility of signal analysis.

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