Heaven's Light is Our Guide

DEPARTMENT OF ELECTRONICS AND TELECOMMUNICATION ENGINEERING

Rajshahi University of Engineering & Technology, Bangladesh

Noise Reduction from Electrocardiogram signal based on adaptive filter using LMS (least mean square) and DLMS (delay least mean square) algorithm.

Author
Rituparna Debnath Ritu
Roll No.: 1504029

Supervised by
Sham Datto
Assistant professor
Department of Electronics & Telecommunication Engineering
Rajshahi University of Engineering & Technology

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Rituparna Debnath Ritu

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CERTIFICATE

This is to certify that the thesis work entitled ***"Noise Reduction from Electrocardiogram signal based on adaptive filter using LMS (least mean square) and DLMS (delay least mean square) algorithm."*** *is carried out by Rituparna Debnath Ritu, Roll no. 1504029 under my supervision in Department of Electronics & Telecommunication Engineering of Rajshahi University of Engineering & Technology.*

Supervisor

…………………………..

Sham Datto
Assistant Professor
Dept. of Electronics & Telecommunication Engineering
Rajshahi University of Engineering & Technology
Rajshahi-6204

External Examiner

…………………………..

Head

……………………………..

Dr. Md Munjure Mowla
Associate Professor
Dept. of Electronics & Telecommunication Engineering
Rajshahi University of Engineering & Technology
Rajshahi-6204

ABSTRACT

The electrocardiogram (ECG) is the recording of the electrical potential of heart versus time. The analysis of ECG signal has great importance in the detection of cardiac abnormalities. The ECG signals are often contaminated by noise from diverse sources. Noises that commonly disturb the basic ECG are power line interference, instrumentation noise, external electromagnetic field interference, noise due to random body movements and respirational movements. These noises can be classified according to their frequency content. It is essential to reduce these disturbances in ECG signal to improve accuracy and reliability.

Removal of noises from respiratory signal is a classical problem. In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the respiratory and other biomedical signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. This paper focuses on (i) model respiratory signal with second order auto regressive process. Then randomly generated noises have been mixed with respiratory signal and nullify these noises using various adaptive filter algorithms (ii) to remove motion artifacts and 50Hz Power line interference using various adaptive filter algorithms. Different types of adaptive and non-adaptive digital filters have been proposed to remove these noises. The LMS and DLMS algorithm are used to reduce the noise. The noises are power line interference and motion artifacts generated noise. The value of step size basically indicates the suitability of algorithms. Select a suitable value for step size and running the algorithms and determine the original ECG signal as much as possible.

At the end of this paper, a performance study has been done between these algorithms based on various step sizes. It has been found that there will be always tradeoff between step sizes and Mean square error.

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List of abbreviations

Term	Elaboration
ECG	Electro Cardiogram
MSE	Mean Square Error
LMS	Least Mean Square
DLMS	Delay Least Mean Square
FIR	Finite Impulse Response
ANC	Adaptive Noise Canceller
NLMS	Normalize Least Mean Square
RLS	Recursive Least Square
WT	wavelet transform
MABWT	Multi Adaptive Bionic Wavelet Transform
FFT	First Fourier Transform
PSNR	Peak signal to noise ratio

CHAPTER 1

Introduction

1.1 Electrocardiogram

ECG signal is a biomedical signal that expresses information about the electrical activity of human heart. ECG is the record of the electrical potentials produced by the heart. It also presents the structure and function of heart. The ECG signal and heart rate reflects the cardiac health of human heart. Any disorder in heart rate or rhythm or change in the morphological pattern of ECG signal is an indication of cardiac arrhythmia. Every portion of ECG is very essential for the diagnosis of different cardiac problems. The ECG is acquired by a non-invasive technique, i.e. placing electrodes at standardized locations on the skin of the patient [1].

1.2 Generation of ECG

An ECG machine is a machine that is used to perform electrocardiography, and creates the electrocardiogram. The first electrocardiographs are electrically primitive compared to today's machines. The fundamental component to electrocardiograph is the instrumentation amplifier, which is responsible for taking the voltage difference between leads and amplifying the signal. ECG voltages measured across the body are on the order of hundreds of microvolts up to 1 millivolt. This low voltage necessitates a low noise circuit and instrumentation amplifiers are key. Early electrocardiographs were constructed with analog electronics and the signal could drive a motor to print the signal on paper. Today, electrocardiographs use analog to digital converter to convert to a digital signal that can then be manipulated with digital electronics. This permits digital recording of ECGs and use on computers.

In a conventional 12-lead ECG, ten electrodes are placed on the patient's limbs and on the surface of the chest. The overall magnitude of the heart's electrical potential is then measured from twelve different angles ("leads") and is recorded over a period of time (usually ten seconds). In this way, the overall magnitude and direction of the heart's electrical depolarization is captured at each moment throughout the cardiac cycle. 50 Hz power is used to produce the real ECG signal.

1.3 Observation of noises

The amplitude and duration of ECG signal is usually despoiled by different noises. In clinical environment during acquisition, the ECG signal encounters various types of artifacts. The ones of primary interest are power line interference, external electromagnetic field interference, noise due to random body movements and respirational movements, electrode contact noise, electromyography (EMG) noise, and instrumentation noise. These noises degrade the signal quality, frequency resolution and strongly affect the morphology of ECG signal containing important information. Many methods have been implemented to remove the noise from noisy ECG signal.

Mainly de-noising two types of noise such as 'additive white Gaussian noise' which is generated by power line interference and frequently change of frequency and 'random noise' that is generated by muscles artifacts, blood speed, random body movement etc. These types of noise interrupt diagnosing the cardiac activities. So, some denoising technique such as LMS (least mean square), DLMS (delay least mean square) for denoising that noisy signal used by us. The above two noise reduction technique is used and identify the real ECG signal.

1.4 Objective

The basic objective of the thesis is to eliminate artifacts from the ECG signal with the efficiency. The objectives are:

- Detect noises that originates into ECG signal.
- Classify them into various category.
- Manipulate adaptive filter and make that filter capable of reducing the noise.
- Define LMS (least mean square) and DLMS (delay least mean square) algorithm based on adaptive filter.
- At last reduce the noise from ECG and make more effective signal.

1.5 Thesis contain:

An ECG signal is being taken which is contaminated with various types of noise. Those noises are filtered by adaptive filter. In adaptive filtering, various types of algorithm are operates. Here LMS (least mean square) and DLMS (delay least mean square) algorithm is used for its simplicity and expected behavior, but the settlement must be made between the convergence (tracking) speed and the steady-state error. This is because the LMS algorithm updates the adaptive filter coefficients with a term whose magnitude is proportional to the so-called step size μ. To obtain the fast convergence speed, μ has to be relatively large but using a large μ produces a large steady-state error (accuracy rate). To obtain the small steady-state error, μ has to be relatively small but using a small μ makes the convergence very slow. So a reliable value of μ is obtained for which the convergence speed and steady state error (accuracy rate) is equally merged. After evaluating the proper value of step size μ, then the main algorithm has to run. For this algorithm FIR (finite impulse response) technique is used. At last observe the de noising output signal.

1.6 Conclusion:

This thesis is focused on the importance of noiseless ECG signal. By following the described method in processing the ECG, it is hoped to see accurate, robust and more advanced tools in cardiac care. A proper tradeoff is maintained between computational complexity and convergence rate. And this will lead to put an end to heart disease which is the number one killer.

CHAPTER 2

Literature review

2.1 Introduction

The field of adaptive filter's application is highly developed with a very big volume of literature. In this section, efforts will be made to report some of these works.

The initial works on adaptive filtering applications can be outlined back in the nineteen forty centuries. In that time the Least Mean Square (LMS) algorithm was designed by Widrow and Hoff in their study of a pattern recognition scheme known as the adaptive linear threshold logic element in [2]. The LMS algorithm and the idea of stochastic approximation method established by Robbins and Monro in statistics for solving sequential parameter estimation problems are thoroughly related with each other [3].

The basic difference between them is that in case of LMS scheme, the algorithm parameter, (i.e., step size) which is used to adjust the correction applied to the tap weight vector from one iteration to the next, is held constant, whereas in stochastic estimate methods the step size is preserved to be inversely proportional to time [4]. The investigational results showed that the adaptive lattice filters is more advantageous than LMS transversal filter, which makes them more preferable adaptive noise canceller (ANC) filter structure if the improved computational cost can be established. A comparative study of the presentations of adaptive filtering algorithms was showed in [5].

2.2 Existing researches

ECG noise cancellation has long mystified for the research community. Normal noise decreasing methods are based on the typical filtering process techniques [6,7]. The ANC based on the Normalized LMS (NLMS) algorithm has a higher convergence rate than the algorithm recycled in normalized LMS algorithm [8]. The NLMS algorithm is also founded on a fixed step size as used in the LMS algorithm.

Lope et.al [9] used kalman filter for cancelling the noise from ECG signal. The Kalman filter is a recursive predictive filter that is built on the use of the recursive algorithms and the state space model techniques. The Kalman filter is advanced with a set of mathematical equations that implements a predictor-corrector type estimator. It is an optimal data processing algorithm in the sense that it reduces the estimated error covariance when some supposed conditions are met. RLS is also a type of algorithm which have quickly convergence ability The RLS algorithm procedures the signal in overlapping blocks of samples. This increases the computational complexity and makes it harder to be implemented. The filter weights are updated as follows in [10]. The RLS method is also more expensive and complex in implementation. For its complexity and expensiveness this method is avoided.

Jagtap et.al [11] implemented high pass, low pass window-based FIR filters using Rectangular, Hamming, Hanning, Kaiser windows for noise reduction in electrocardiogram. The order of filter is taken as 100. They have examines the performance by comparing signal power before and after filtration. With this order, the FIR filter with rectangular window has sharp attenuation and pulsation present in the stop band and pass band. The phase response of rectangular was linear and the filter was found to be stable, in comparison to others.

Adaptive algorithms i.e., LMS and RLS for noise cancellation is expressed by Singh [12]. According to their paper, the RLS algorithm based adaptive filter has better performance. In the process of digital signal processing, often to deal with some unforeseen signal, noise or time-varying signals, if only by a two FIR and IIR filter of fixed coefficient can't achieve optimal filtering. Under such circumstances, they must design adaptive filters, to track the changes of signal and noise. Adaptive Filter is that it uses the filter parameters of a moment ago to automatically adjust the filter parameters of the present moment, the results are shown in Figure 2.1 & 2.2.

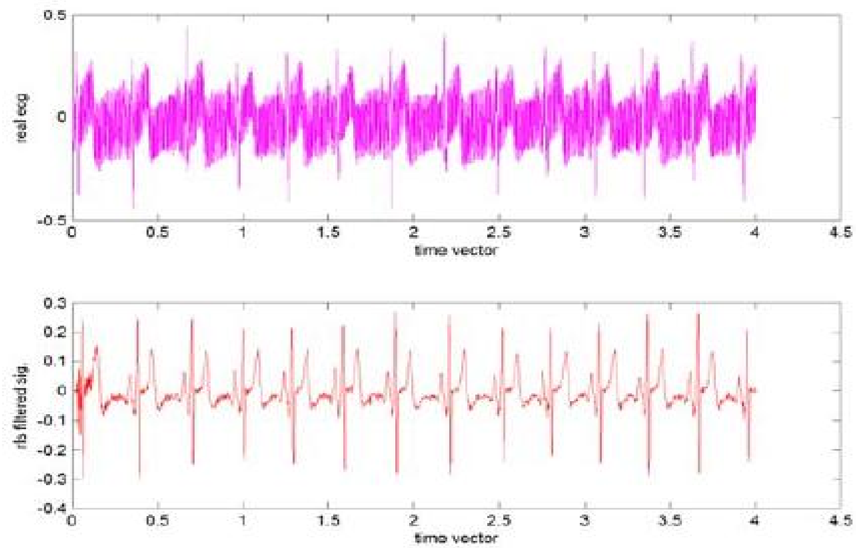


Figure 2.1: The RMS filter input (signal with noise) and filtered signal [12].

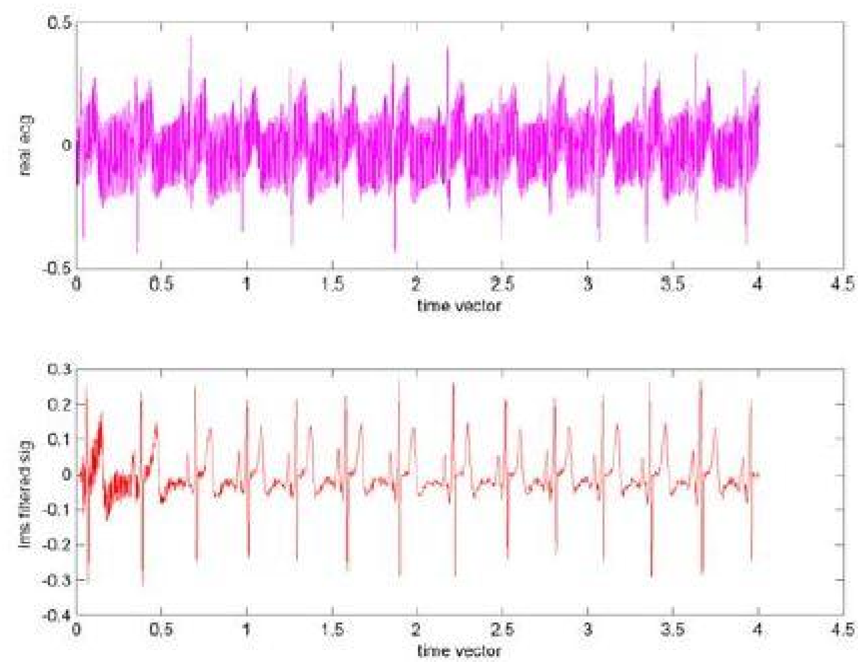


Figure 2.2: The LMS filter input (signal with noise) and filtered signal [12].

The simulation result shown Figure 2.2 replies that LMS algorithm give good results in comparison to RLS algorithm in the area of Biomedical Signal Processing to cancel the noise. To complete the task of noise reduction LMS filtering results is relatively good, the requirements length of filter is relatively short, it has a simple structure and small operation and is easy to realize hardware.

Rahman [13] used several simple and efficient signs based normalized adaptive filters for cancelation of noise in (ECG) signals, which are computationally superior having multiplier free weight update loops in. The proposed implementation is suitable for applications such as biotelemetry, where large signal to noise ratios with less computational complexity are required. It is so much difficult to fixed any filter which is best to remove noise from ECG. Results of simulation in MATLAB are presented and a critical analysis is made on the basis of convergence rate and signal to noise ratio, computational time among the filtering technique. The results are shown in figure 2.3.

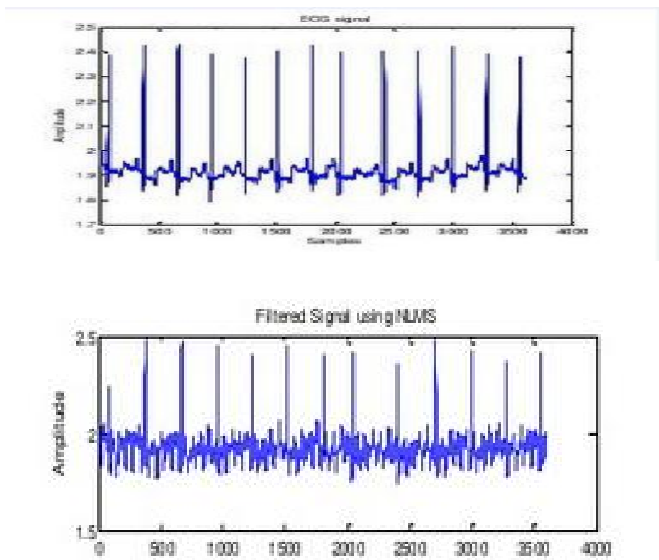


Figure 2.3: Original ECG and Filtered ECG signal using NLMS [13].

Chang et.al [14] compared the adaptive algorithm performance for noise cancellation with and without using the external reference in “Cancellation of high-frequency noise in ECG signals using Adaptive filter without external reference”. The adaptive filter with reference is often ineffective due to the fact that the reference signal cannot be well correlated with the noise part in the primary input. Therefore, the adaptive filter without external reference was implemented.

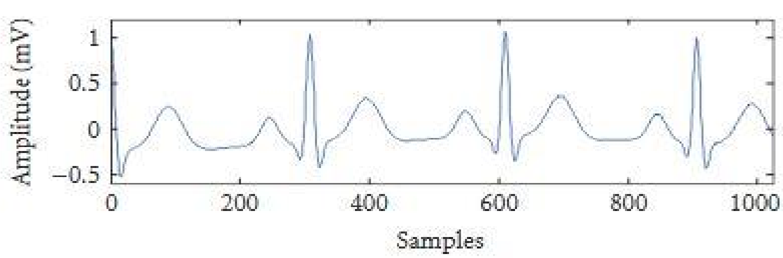
Over the past several years, methods based on the wavelet transform (WT) have also received a great deal of attention for the denoising of signals that possess multi tire solution characteristics such as the ECG [15]– [20].

Gowri et.al [16] presented that when acquiring the Electrocardiogram (ECG) signal from the person, it should be preprocessed before sending to the analyst for taking decision of the signal, because signal should be affected with various artifacts. For numerous applications of noise cancellation in the corrupted signals, adaptive filters play important role. The various artifacts which commonly occur in the acquisition of ECG signals are physiological and non- physiological noises, those are main supply power line interference, muscle artifact, electrode motion artifact and base line wander noises. The adaptive Least Mean Square (LMS) algorithm provides a low convergence rate, so that for fast convergence rate and reduced noise, in this paper an efficient Recursive Least Square algorithm is considered, for removing of power line noise and muscle noise. For double validation of the signal, and for high Signal to Noise Ratio (SNR), fast convergence rate, is achieved by using LMS to RLS adaptive algorithm at the cost of additional computations.

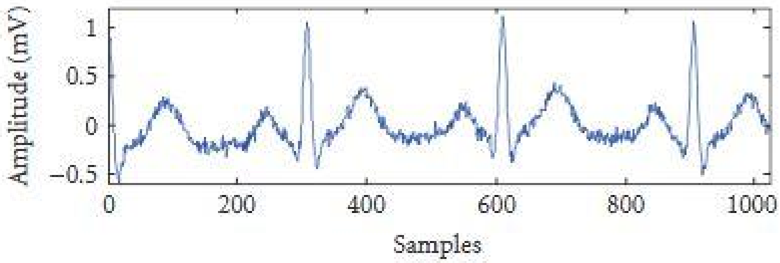
In the recent wavelets' literature, one often encounters the term Denoising, describing in an informal way various schemes which attempt to reject noise by damping or thresholding in the wavelet domain. For example, in the special "Wavelets" issue of IEEE Trans. Information Theory, articles by Mallat and Hwang and by Semoncelli, Freeman, Adelson and Heegr use this term; at the Toulouse conference on wavelets and application. It was used in oral communication by coifman the more prosaic term "noise reduction" has been used by Lu [17].

They propose here a formal interpretation of term "de noising" and show how wavelet transform may be used to optimally "de noise" in the interpretation. Moreover this "de noising" property signals near complete success in an area where many non-wavelets methods have meet only partial success.

Popescu et.al [18] present a new modified wavelet transform, called the multi adaptive bionic wavelet transform (MABWT), that can be applied to ECG signals in order to remove noise from them under a wide range of variations for noise. By using the definition of bionic wavelet transform and adaptively determining both the center frequency of each scale together with the We present a new modified wavelet transform, called the multi adaptive bionic wavelet transform (MABWT), that can be applied to ECG signals in order to remove noise from them under a wide range of variations for noise. By using the definition of bionic wavelet transform and adaptively determining both the center frequency of each scale together with the Open image in new window-function, the problem of desired signal decomposition is solved. Applying a new proposed thresholding rule works successfully in de noising the ECG. Moreover by using the multi adaptation scheme, low pass noisy interference effects on the baseline of ECG will be removed as a direct task. The method was extensively clinically tested with real and simulated ECG signals which showed high performance of noise reduction, comparable to those of wavelet transform (WT). Quantitative evaluation of the proposed algorithm shows that the average SNR improvement of MABWT is 1.82 dB more than the WT-based results, for the best case. Also, the procedure has largely proved advantageous over wavelet-based methods for baseline wandering cancellation, including both DC components and baseline drifts. -function, the problem of desired signal decomposition is solved. Applying a new proposed thresholding rule works successfully in de noising the ECG. Moreover by using the multi adaptation scheme, low pass noisy interference effects on the baseline of ECG will be removed as a direct task. The method was extensively clinically tested with real and simulated ECG signals which showed high performance of noise reduction, comparable to those of wavelet transform (WT). Quantitative evaluation of the proposed algorithm shows that the average SNR improvement of MABWT is 1.82 dB more than the WT-based results, for the best case. Also the procedure has largely proved advantageous over wavelet-based methods for baseline wandering cancellation, including both DC components and baseline drifts. The whole results are following below into Figure 2.4.



(a)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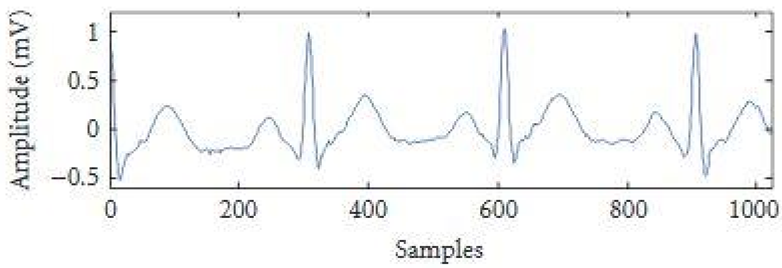
Samples

(b)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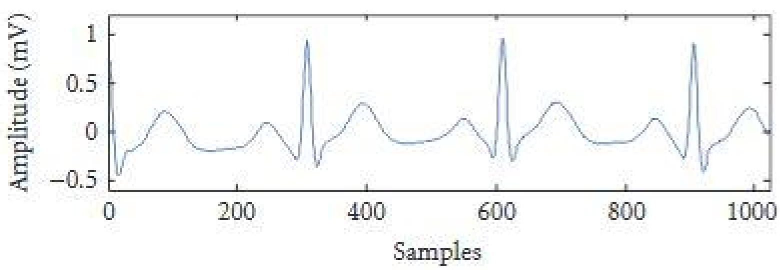
(c)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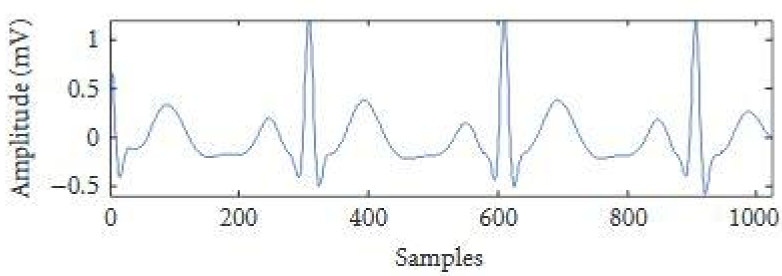
(d)


Amplitude (mV)
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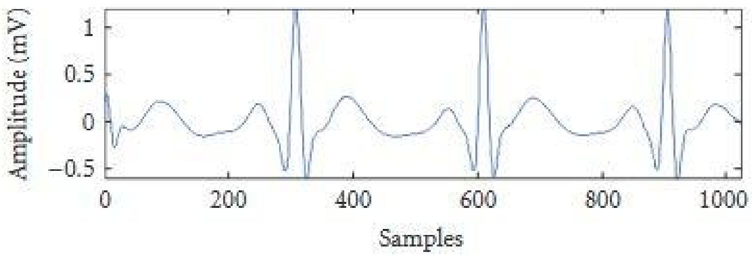
(e)



(f)

Figure 2.4: Typical results of different methods for an input simulated signal of 6 dB (a) Clean ECG, (b) noisy input signal, (c) WT (hard), (d) WT (soft), (e) MABWT (hard), and (f) MABWT (soft) [18].

Agnate et.al [19] expressed that Signal processing and data analysis are widely used methods in a biomedical research. In recent years, detection of cardiovascular abnormalities in patients can be achieved by using electrocardiogram (ECG) recording. In this paper, a fuzzy-based multi-objective algorithm using Fast Fourier Transform (FFT) is proposed. Initially, an effective FFT is used to extract the feature points in ECG signals, such as PQRST wave's amplitude and wave function and then the proposed multi-objective genetic algorithm is used to classify the abnormality of heart patient. Basically, the ECG behavior depends on various factors such as age, physical condition of patients and the surrounding environment. The efficient detection of abnormalities (e.g. arrhythmia and myocardial abstraction) can be achieved by initializing the above-mentioned factors and maintaining a database containing previously attributed signals, such MIT-BIH arrhythmia. The present study provides efficiency of around 98.7% in detection of abnormalities in patients. The signals are shown in Figure 2.5 & 2.6.

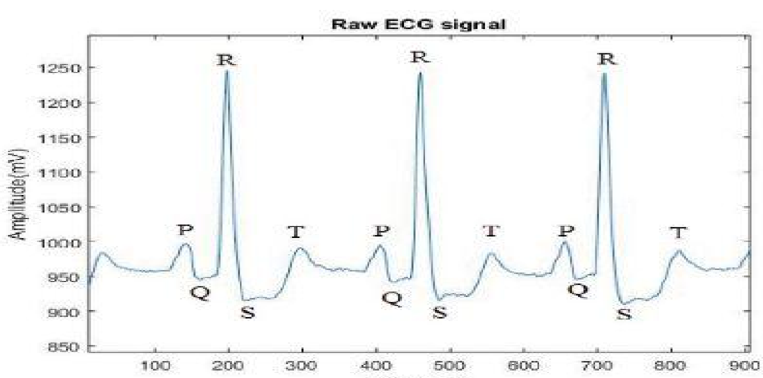


Figure 2.5: Raw ECG signal [19].

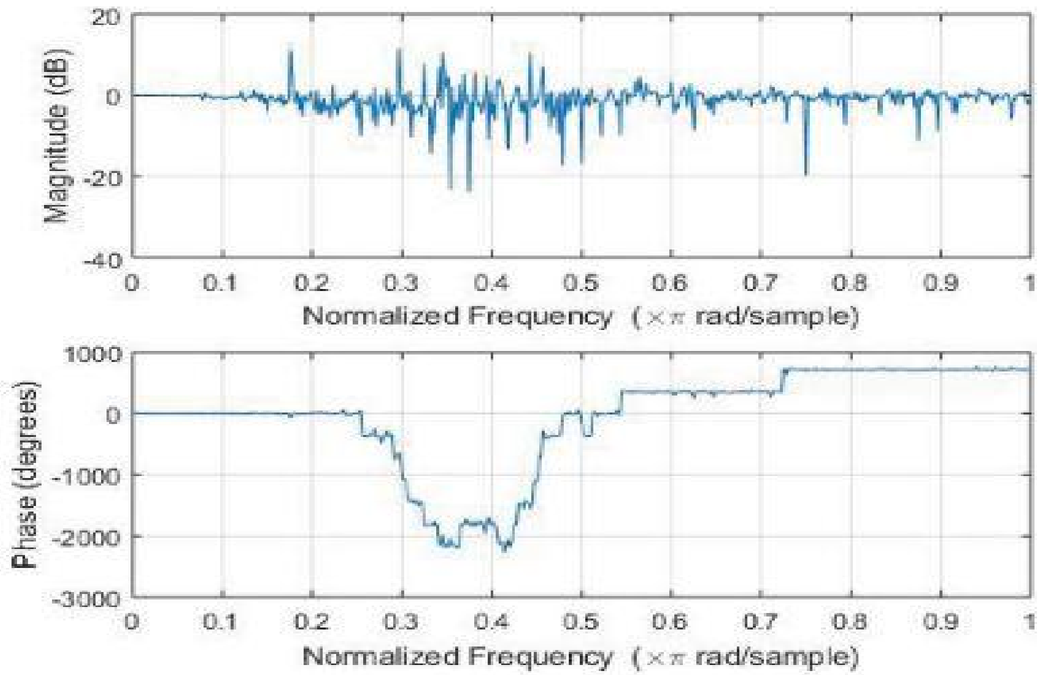


Figure 2.6: Resultant ECG signal [19].

Sayadi et.al [20] present a new modified wavelet transform, called the multiadaptive bionic wavelet transform (MABWT), that can be applied to ECG signals in order to remove noise from them under a wide range of variations for noise. By using the definition of bionic wavelet transform and adaptively determining both the center frequency of each scale together with the T-function, the problem of desired signal decomposition is solved. Applying a new proposed thresholding rule works successfully in denoising the ECG. Moreover, by using the maladaptation scheme, lowpass noisy interference effects on the baseline of ECG will be removed as a direct task. The method was extensively clinically tested with real and simulated ECG signals which showed high performance of noise reduction, comparable to those of wavelet transform (WT). Quantitative evaluation of the proposed algorithm shows that the average SNR improvement of MABWT is 1.82 dB more than the WT-based results, for the best case. Also the procedure has largely proved advantageous over wavelet-based methods for baseline wandering cancellation, including both DC components and baseline drifts.

Tiwari et.al [21] have applied an optimal wavelet basis function for denoising of an ECG signal In the experimental results have revealed suitability of Daubechies mother wavelet of order 8 to be the most appropriate wavelet basis function for the denoising application. Over the years (ECG) signal has been used to assess the cardiovascular condition of humans. In practice, real time acquisition and transmission of the ECG may contain noise signals superimposed on it. In general, the signal processing algorithms employed for denoising provide optimal performance and eliminate the high frequency noise between any two beats contained in a continuous ECG signal. Despite their optimal performance, the signal processing algorithms significantly attenuate the peaks of characteristics wave of the ECG signal. This paper presents a selection procedure of mother wavelet basis functions applied for denoising of the ECG signal in wavelet domain while retaining the signal peaks close to their full amplitude. The obtained wavelet based denoised ECG signals retain the necessary diagnostics information contained in the original ECG signal. The signals are shown in figure 2.7.

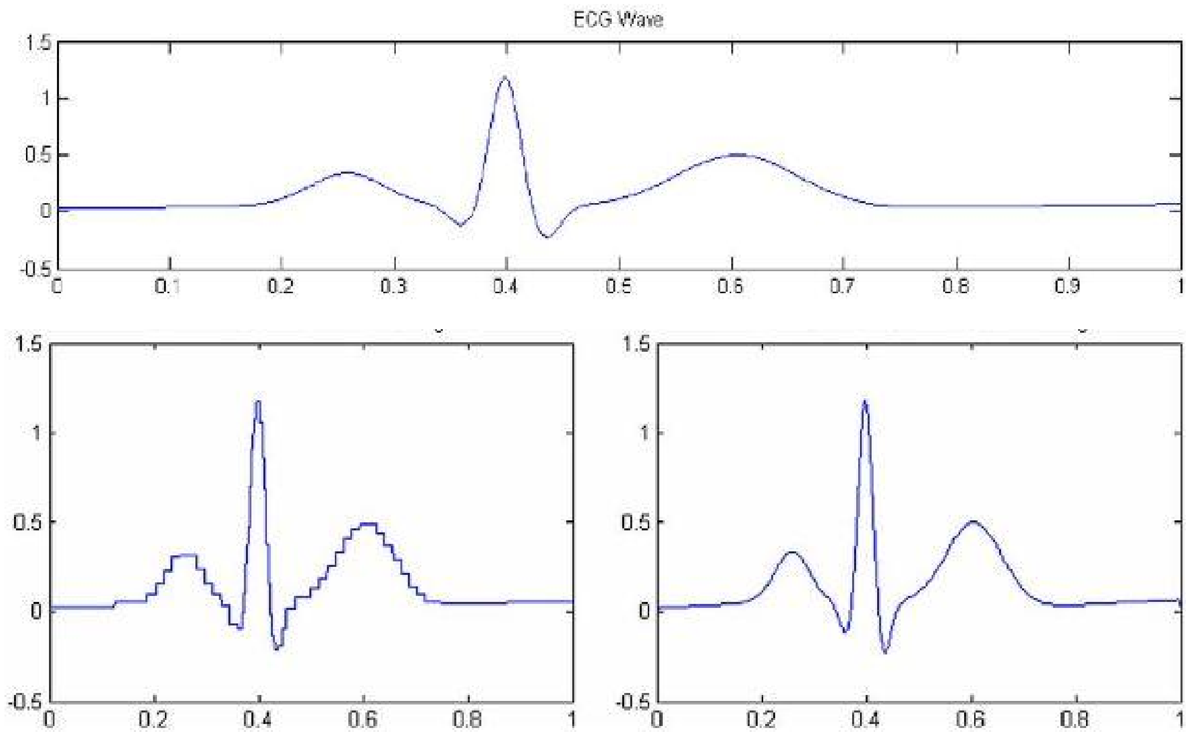


Figure 2.7: MATLAB generated ECG signal and decomposition and reconstruction using Haar and Daubechies (order 8) filter [21].

An efficient denoising scheme for (ECG) signals based on extended Kalman filter (EKF) structure. The basic idea is to overcome the disadvantages of conventional techniques like median filter by utilizing the adaptive nature of EKF structure. For the comparative analysis this paper deployed three important parameters; mean square error (MSE), Peak signal to noise ratio (PSNR), and most importantly RR interval estimation. On the basis of the three parameters a comparative analysis has been presented to explore efficient denoising capability of EKF over median filter. The results obtain indicates that EKF provides very less MSE and very high PSNR as compare to median filter. On the other side the estimated RR interval obtained using EKF is the closest match with original signal RR intervals, while median filter provides so many RR intervals, which are not even presents in the original signal, which is presented by Barros et.al [22]. The results are shown in figure 2.8.

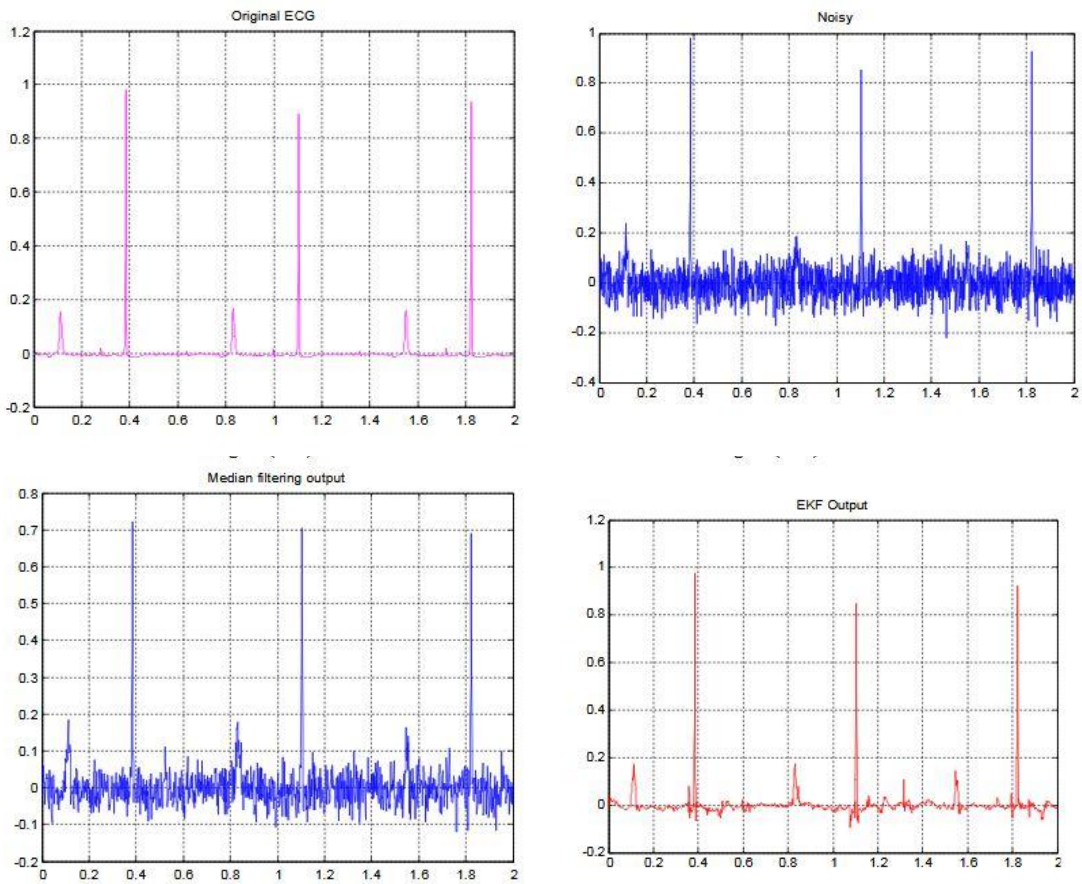


Figure 2.8: The original, noisy, median and EKF output ECG signal [22].

A new measure for quantifying diagnostic information from a multi lead electrocardiogram (MECG) is proposed. This diagnostic measure is based on principal component (PC) multivariate multiscale sample entropy (PMMSE). The PC analysis is used to reduce the dimension of the MECG data matrix. The multivariate multiscale sample entropy is evaluated over the PC matrix. The PMMSE values along each scale are used as a diagnostic feature vector. The performance of the proposed measure is evaluated using a least square support vector machine classifier for detection and classification of normal (healthy control) and different cardiovascular diseases such as cardiomyopathy, cardiac dysrhythmia, hypertrophy and myocardial infarction. The results show that the cardiac diseases are successfully detected and classified with an average accuracy of 90.34%.

Comparison with some of the recently published methods shows improved performance of the proposed measure of cardiac disease classification which is presented by G. D. Clifford [23].

Jan Adamec [24] said that Electrocardiogram (ECG) is continuous recording of electrical signals of heart against time. The analysis of ECG signal is essential and proves important in detecting cardiac peculiarities. Electro cardio graphic signals are nothing but numerous presences of noise added from different sources. Some common noise source that affect or disturb basic electrocardiogram are mainly power line interference, medical operating devices noise and electromagnetic field interference from other sources, noise due to random body movements and breathing movements. Noises are classified on basis of their frequency content and time variation. It is absolutely necessary to reduce these disturbances in ECG signal to improve accuracy and reliability. Noise minimizes after removing high and low frequencies. Basic classification is performed in two class namely abnormal and normal signal. ECG signal gets classified on intervals in PR, RR and QRS width from this decision rules are form. At primary stage abnormal signal of human heart detect cardiac patients. This paper reviews and summarizes about the ECG signal classification.

The results are shown into table: 2.1.

Table 2.1: Nominal value of amplitude & duration of wave.

Features/Interval	Amplitude	Duration
P wave	0.1-0.2mv	80ms
PR	-	120-200ms
QRS complex	1-1.2mv	80-120ms
J point	-	-
ST	80-120	ST interval
T wave	0.12-0.3	160ms
QT	-	290-429ms
U wave	-	-
RR	-	0.2-1.2s

Catalano et.al [25] presented that Digital filters are a very important part of digital signal processing, especially for biomedical signal processing. In fact, their extraordinary performance is one of the key reasons that signal processing has become so popular. Digital filters have two primary functions: signal separation and signal restoration. Signal separation is needed when a signal has been contaminated with interference, noise, or other undesirable signals. In this work, two methods, that is, wavelet and non-local means (NLM) filtering technique is explored for denoising the ECG signal. The noisy ECG signal is synthesized by adding pulse signals and is then denoised at different levels by optimizing different parameters. The experimental results showed that the proposed techniques successfully denoised the noisy ECG signals by selecting appropriate input parameters. Finally, the peak signal to noise ratio (PSNR) and mean square error (MSE) were also evaluated to compare the performance of both evaluated methods. The resulting signal is shown in Figure 2.9.

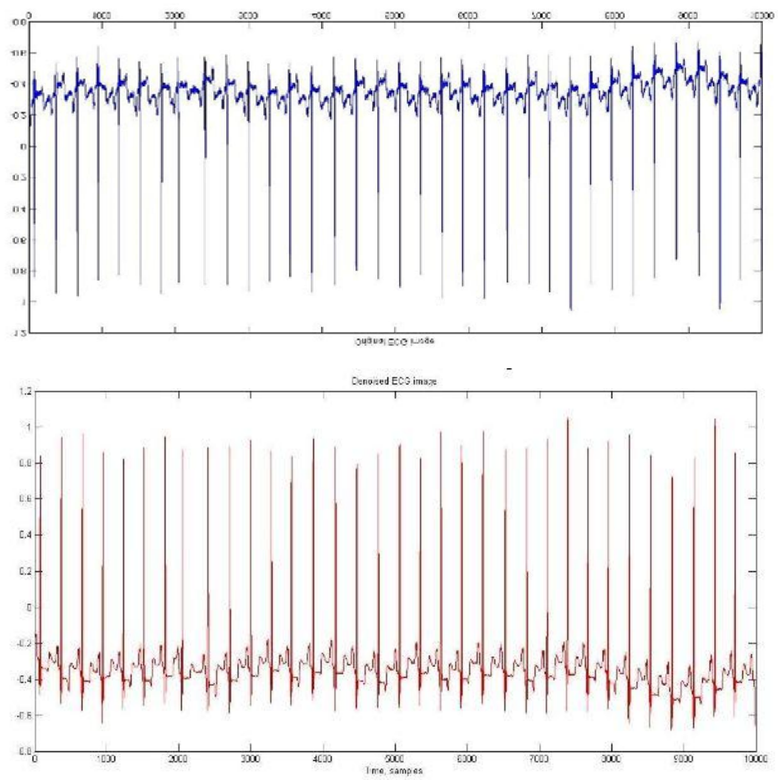


Figure 2.9: Resulting ECG signal [25].

Katz et.al [26] invented that electrocardiogram (ECG) is a diagnosis tool that recorded the electrical activity of the heart by using several electrodes attached to the body surface. But the amplitude and duration of ECG signals are usually corrupted by different noises therefore in this study different noises like power line interference (PLI), baseline wander (BW), and random noise are analyzed. Random noise is also called as electromyographic (EMG) noise. These noises misguide the diagnosis of the heart which is not desired. To avoid this problem caused by different noises, removal of these noises has become essential. The adaptive filter has been proposed to filter these noises from the ECG signal. There are various adaptive filtering algorithms are used to filter ECG signals. The three basic adaptive filtering algorithms are Least Mean Square (LMS), Normalized Least Mean Square (NLMS) and Constrained Stability Least Mean Square (CSLMS) algorithms are applied to remove these noises. In this paper, we have applied these algorithms on ECG signals corrupted with various noises and compared its performance with the LMS, NLMS and CSLMS algorithms. For output performance measurement different output parameters are used such as signal to noise ratio (SNR), percent root mean square difference (PRD) and mean square error (MSE). The result is in Figure 2.10.

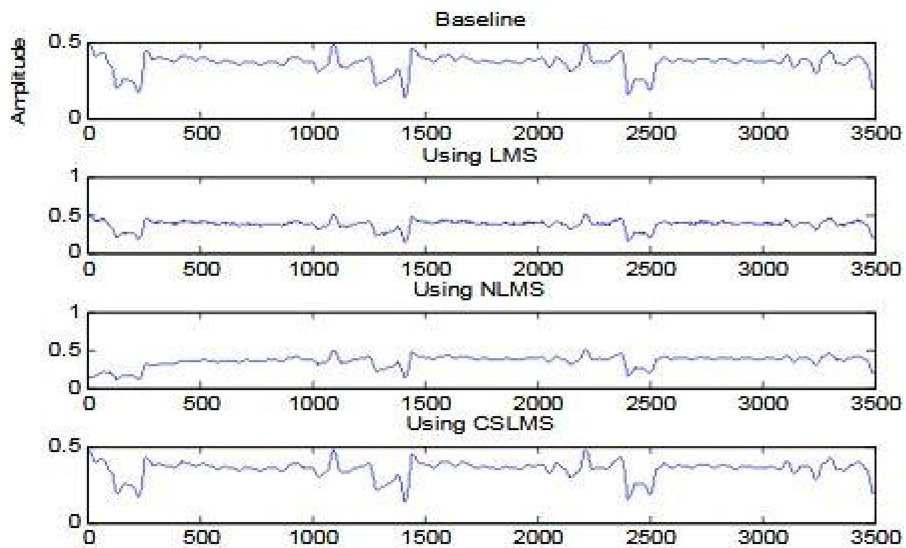


Figure 2.10: LMS, NLMS, CSLMS filtering output [26].

The 50 Hz power line is one of the main sources of interference in ECG signal measurement, and it distorts the original ECG signal while recording. Recently, adaptive filtering has become one of the effective and popular methods for the processing and analysis of the ECG signal. In this study, he has used adaptive filters to remove the power line interference from the ECG signal. He has used different adaptive filter algorithms, such as, Least-Mean-Square (LMS), Block LMS (BLMS), Delay LMS (DLMS), Adjoint LMS, Filtered-X (XLMS), Normalized LMS (NLMS) and Fast Fourier Transform BLMS (FFT BLMS).We have used the Signal Processing Toolbox of the mentioned algorithms built in MATLAB®. It reveals that among all the adaptive filters, the adaptive NLMS filter removes the 50 Hz power line interference more effectively replied by Maniruzzaman [27]. The output is shown in Figure 2.11.

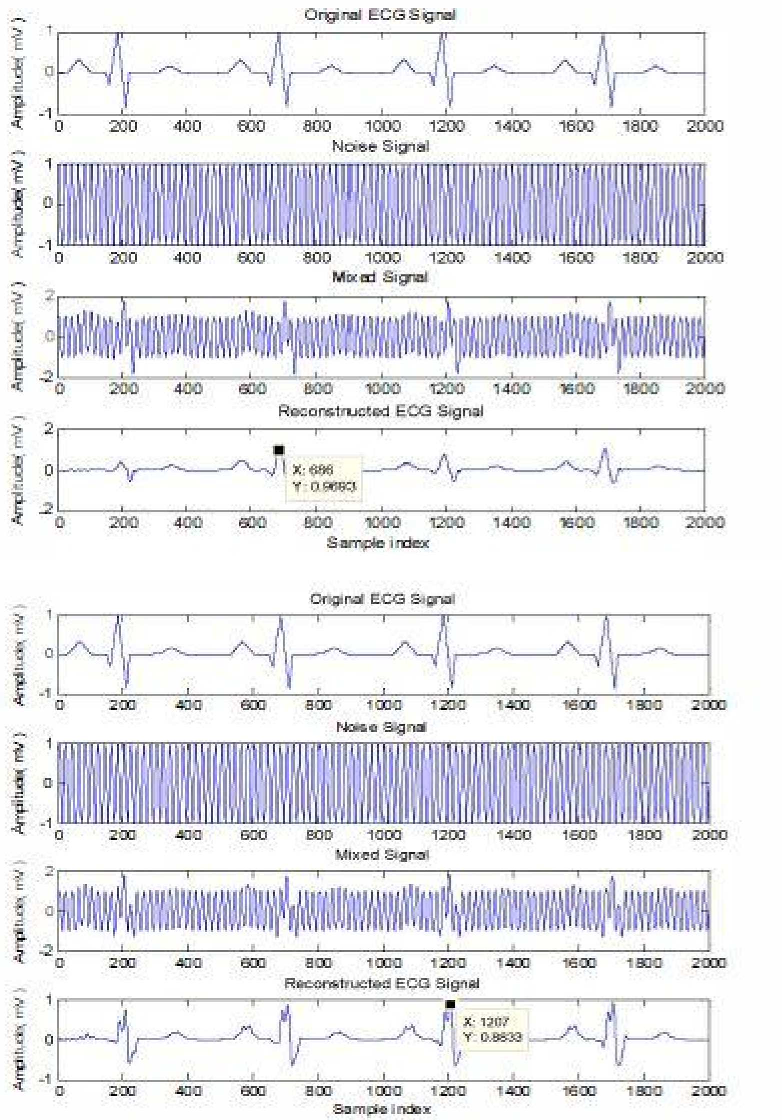


Figure 2.11: Reconstructed ECG signal [27].

Guda et.al [28] presents that Electrocardiographic (ECG) signal can be contaminated by diverse forms of noise: baseline wander, 60 Hz power line interference, muscle noise, and motion artifact. 60Hz power line interference can be cancelled using two different approaches; an adaptive filter or notch filters. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the noisy ECG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. In this paper we present a MATLAB simulation comparison between different adaptive filter algorithms; Least Mean Square (LMS), Normalized LMS (NLMS), Variable Step size LMS

(VSLMS), Recursive Least Square (RLS) and Blind LMS. The comparison is carried out in terms of both, MSE and the algorithm convergence rate in. The output is shown in figure 2.12.

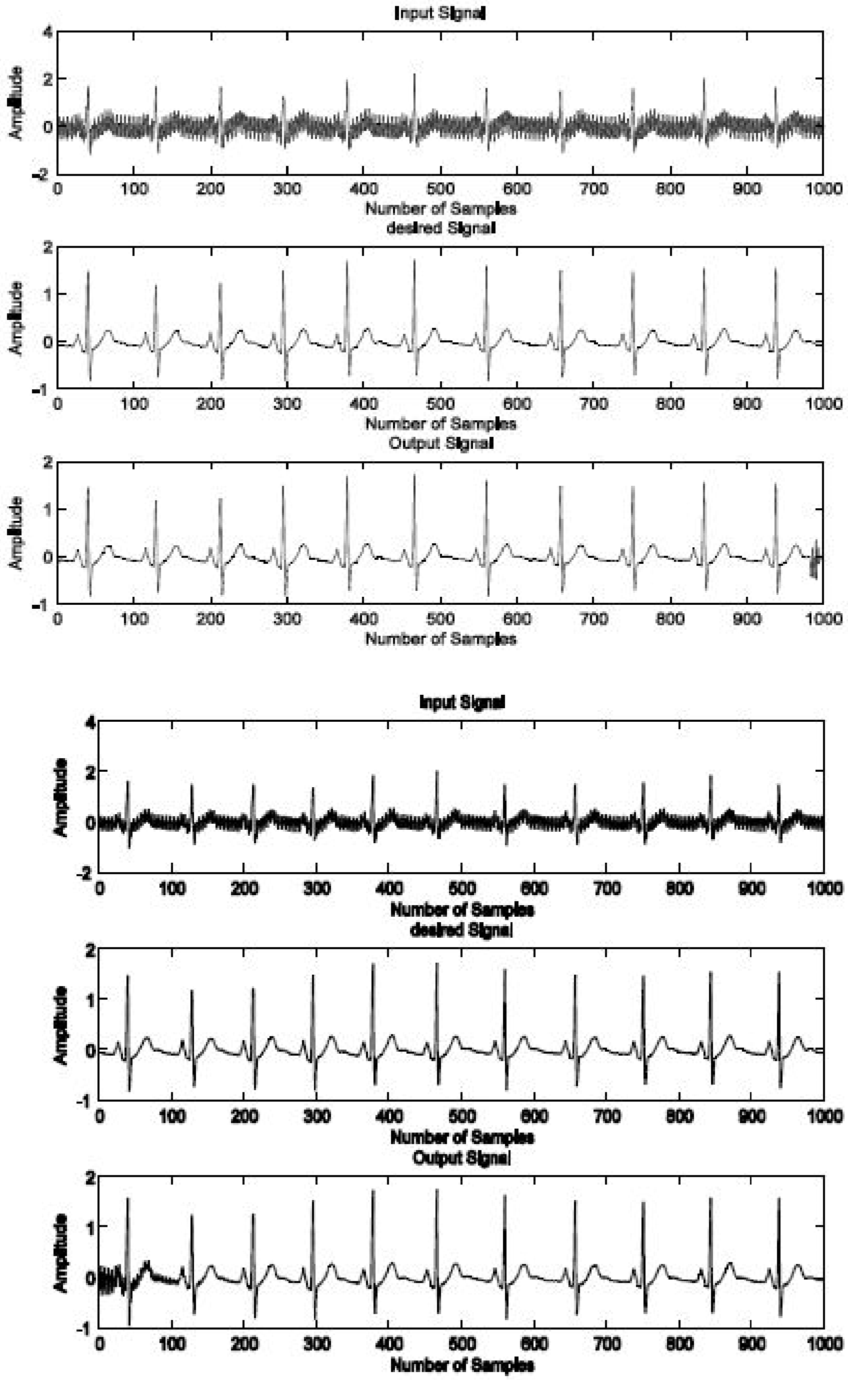


Figure 2.12: LMS, NLMS, VSLMS, BLMS ECG output [28].

PAN has [29] developed a real-time algorithm for detection of the QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital analyses of slope, amplitude, and width. A special digital bandpass filter reduces false detections caused by the various types of interference present in ECG signals. This filtering permits use of low thresholds, thereby increasing detection sensitivity. The algorithm automatically adjusts thresholds and parameters periodically to adapt to such ECG changes as QRS morphology and heart rate. For the standard 24 h MIT/BIH arrhythmia database, this algorithm correctly detects 99.3 percent of the QRS complexes.

In voice communication systems, Afroz indicates in [30] that noise cancellation using adaptive digital filter is a renowned technique for extracting desired speech signal through eliminating noise from the speech signal corrupted by noise. In this paper, the performance of adaptive noise canceller of Finite Impulse Response (FIR) type has been analyzed employing NLMS (Normalized Least Mean Square) algorithm. An extensive study has been made to investigate the effects of different parameters, such as number of filter coefficients, number of samples, step size, and input noise level, on the performance of the adaptive noise cancelling system. All the results have been obtained using computer simulations built on MATLAB platform. The output is shown in Figure 2.13.

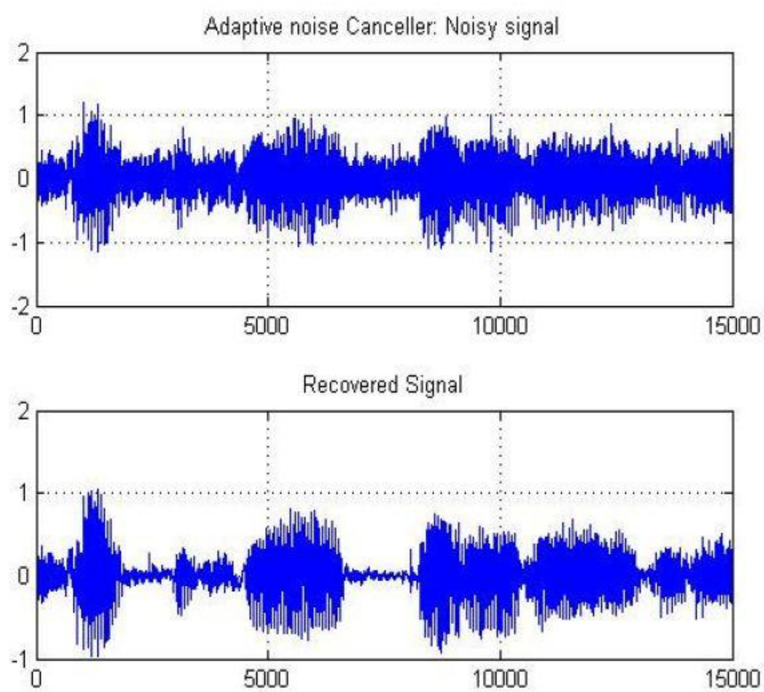


Figure 2.13: Noisy and Recovered signal [30].

2.3 Conclusion

From the above discussion, the authors used different method and algorithm to reduce noise from the original ECG signal. All the processes are performed at 50 Hz power supply frequency. All the results obtained using computer simulations built on MATLAB software in de-noising purpose. Most of the authors used LMS, DLMS, NLMS, BLMS, wavelet transform etc. algorithm.

CHAPTER 3

Noise reduction from ECG signal using adaptive filtering technique

This chapter addresses about the biological phenomenon of human heart which can be affected by various types of noise, originates from power line interference, muscles artifacts, blood speed, electrode contact noise etc. Our main objective is to denoising the main ECG signal using adaptive filtering technique. Which help us to determine to identify fresh and more acceptable main ECG signal by eliminating the noise as much as possible.

50 Hz power line is one of the main sources of interference in ECG signal measurement, and it changes the original ECG signal while recording. Recently, adaptive filtering has become one of the effective and popular methods for the detecting and analysis of the ECG signal. In this study, adaptive filters are used to remove the power line interference from the ECG signal. Different adaptive filter algorithms, such as, Least-Mean-Square (LMS), Delay LMS (DLMS) are used. The Signal Processing Toolbox of the declared algorithms built in MATLAB® is used by us. It reveals that among all the adaptive filters, the adaptive LMS filter removes the 50 Hz power line interference more effectively.

During the analysis of arrhythmia or myocardial infraction, the 50 Hz power line noise can affect the ECG signal. The frequency range of ECG signal is generally 0.05 Hz to 100 Hz, and, that of the power line interference is 50 Hz which lies in the ECG signal band. So, it has become very vital to remove the power line interference from the ECG signal. Different types of digital filters (FIR filter) have been used to solve the problem [31]. However, it is difficult to apply these filters with fixed coefficients to reduce the power line interference, because the ECG signal is known as a non-stationary signal or wave. Recently, adaptive filtering has become one of the effective and popular methods for the processing and analysis of the ECG signal [32]. It is well known that adaptive filters with LMS algorithm show good performance for processing and analysis of the most of the biomedical signals which are non-stationary. And in this study, we have used adaptive filters to remove the power line interference from the ECG signal.

3.1 Basics of ECG and artifacts

This Chapter explains basics of electrocardiogram, the generation of heart beat and morphology of ECG waveform. Artifacts that commonly appear in ECG signal during acquisition are elaborately discussed.

3.1.1 Electrocardiogram

The ECG is a bioelectric signal, which records the electrical activity of heart versus time. Therefore, it is an important diagnostic tool for assessing heart function [24]. The ECG is acquired by placing electrodes on the skin of the patient. The ECG signal provides the following information of a human heart [25]:

- Disturbances in heart rhythm and conduction
- Abnormalities in the spread of electrical impulse across the heart
- Information about a prior heart attack
- Sign of coronary artery disease
- Abnormal thickening of heart muscle
- Indication of decreased oxygen delivery to the heart
- Extent and location of myocardial ischemia
- Changes in electrolyte concentrations
- Effects of drugs on the heart

3.1.2 Structure and physiology of heart

The human heart weighs 250- 350 grams and is approximately equal to the size of the fist. It is located anterior to the vertebral column and posterior to the sternum. It is covered by a double-walled sac called the pericardium. The exterior part of this sac is called the fibrous pericardium. This sac protects the heart, anchors its surrounding structures and prevents overfilling of the heart with blood. The outer wall of the human heart is composed of three layers. The outer layer is called the epicardium or visceral pericardium since it is also the inner wall of the pericardium. The middle layer is called the myocardium and is composed of cardiac muscle which contracts. The inner layer is called the endocardium and is in contact with the blood. It also merges with the inner lining (endothelium) of blood vessels and covers heart valves.

The Heart is divided into separate right and left sections by the interventricular septum. Each of these (right and left) sections are again divided into upper and lower compartments known as atria and ventricles respectively. Thus, human heart has four chambers i.e. two superior atria and two inferior ventricles. The atria are the receiving chambers and the ventricles are the discharging chambers as shown in the Fig. 3.1. The atria are attached to the ventricles by fibrous, non-conductive tissue that keeps the ventricles electrically isolated from the atria. The Tricuspid valve separates the right atrium from the right ventricle. The Mitral (also known as the Bicuspid) valve separates the left atrium from the left ventricle.

Oxygen-poor blood from the whole body is received into the right atrium through large veins called the superior and inferior vena cava and flows. The right atrium and the right ventricle together form a pump to the circulate blood to the lungs. The right ventricle then pumps the blood to the lungs where the blood is oxygenated. Similarly, the left atrium and the left ventricle together form a pump to circulate oxygen-enriched blood received from the lungs (via the pulmonary veins) to the rest of the body.

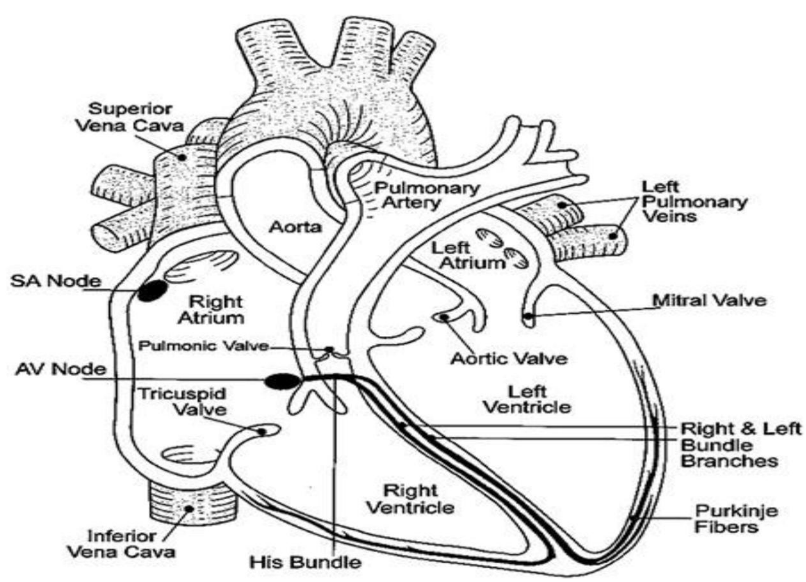


Figure 3.1 Structure of heart.

3.1.3 Generation of heart beat

Some cardiac cells are self-excitable, contracting without any signal from the nervous system. Even if removed from the heart and placed in culture, the cells have the self-excitation property. The electrical potentials for contraction are caused by a group of specialized cells in the heart which control the heartbeat. These cells produce electrical impulses which spread across the heart causing it to contract. The main pacemaker of heart, the Sinoatrial node (SA node), initiates the heart beat by generating an electrical impulse which travels to the left and right atria, causing them to contract (atrial depolarization). Following the start of atrial depolarization, the impulse quickly arrives at the Atrioventricular node (AV node) which is responsible for the contraction of ventricle. The electrical signal next passes through the Bundle of His, diverges into the Right and Left Bundle branches, and spreads through the Purkinje Fibers to the muscles of the left and right ventricle. This causes ventricular depolarization (contraction). The time required for the signal to travel from the AV node to the Purkinje Fibers provides a natural delay of about 0.1 second. This delay ensures that the atria have become completely empty before the ventricles contract. The contraction is followed by ventricular repolarization (recovery) of the cells which were excited during the previous depolarization wave.

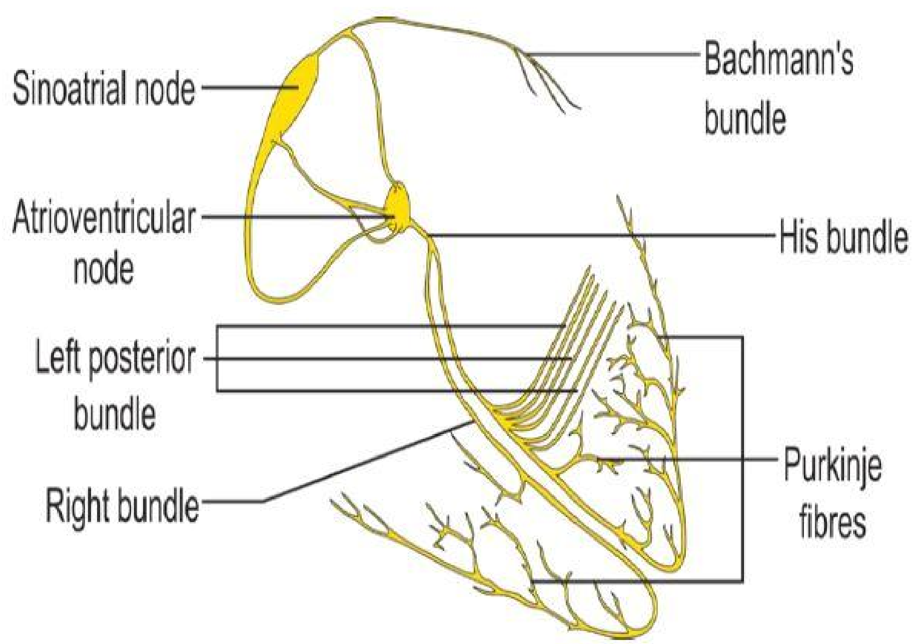


Figure 3.2: Conduction path of electrical potential for heart beat

The SA node creates the electrical impulse which causes the heart to beat, but the Autonomic Nervous System (ANS) controls the heart rate and the strength of heart contractions. The ANS consists of two parts, the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). The Sympathetic nerves increase the heart rate and the contraction force, while the Parasympathetic nerves act in the reverse manner. An idealized conduction of electrical impulse for heart beat is shown in Figure 3.2. A small portion of this electrical potential flows to the body surface. By applying electrodes on the skin at the selected points, the electrical potential generated by this current can be recorded as an ECG signal [33].

3.1.4 ECG morphology

ECG waveform of a normal individual consists of P wave, QRS complex, ST segment, T wave and U wave. The labels of Fig. 2.3 are commonly used in medical ECG terminology.

P wave: When the electrical impulse is conducted from the SA node towards the AV node and spreads from right to left atrium, the depolarization (contraction) of the atria occurs. The depolarization of atria results the P Wave in the ECG.

QRS complex: The QRS complex consists of three waves, sequentially known as Q, R and S. The rapid depolarization of both the ventricles results this complex. The muscles of the ventricles have large muscle mass than that of atria, hence its amplitude is much larger than that of P wave.

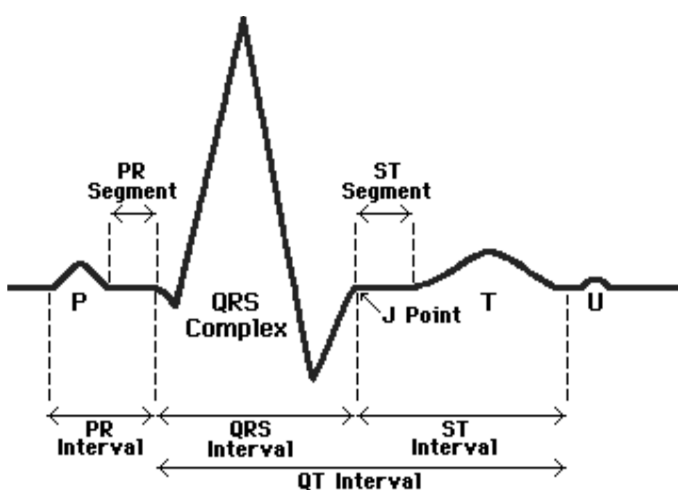


Figure 3.3: ECG waveform

T wave: Ventricular repolarization results the preceding of ST segment and the T wave.

U wave: The origin of U wave is not clear and it is rarely seen. It is probably produced due to the repolarization of the papillary muscles [33].

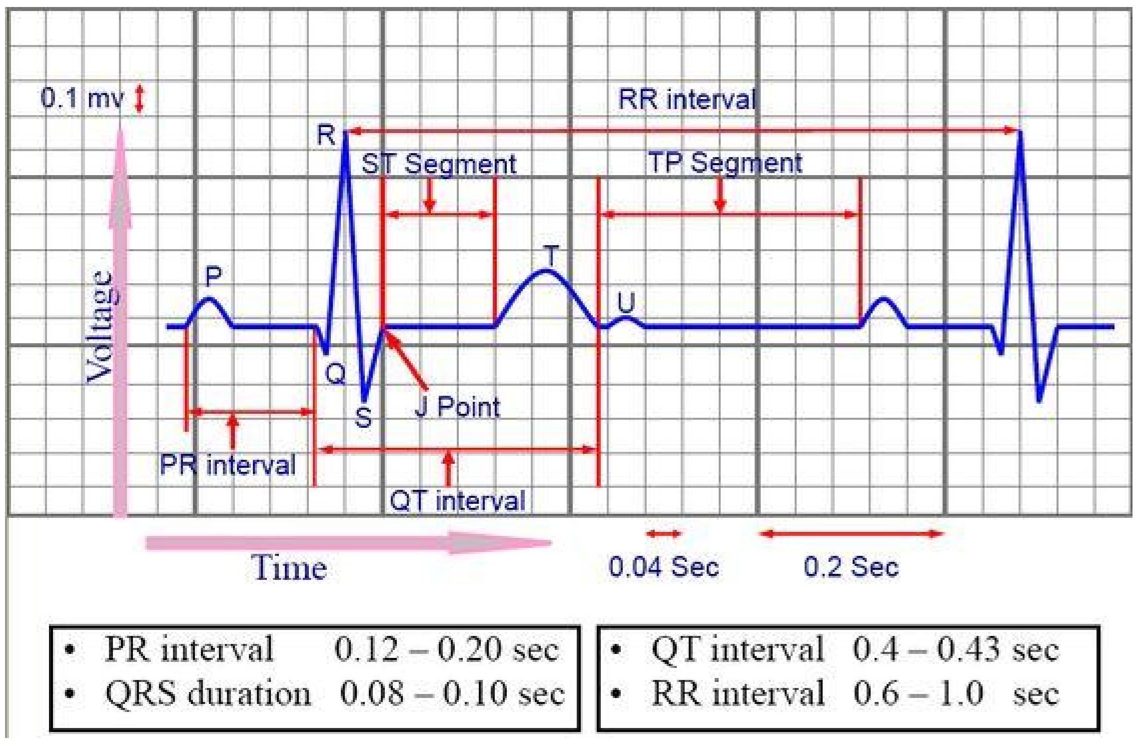


Figure 3.4: ECG intervals

PR interval: Reects the time the electrical impulse takes to travel from the sinus node through the AV node and entering the ventricles. Usually 120 to 200 ms long.

PR segment: Corresponds to the time between the end of atrial depolarization to the onset of ventricular depolarization. Last about 100 ms.

Q wave: Represents the normal left-to-right depolarization of the interventricular septum.

R wave: Represents early depolarization of the ventricles.

S wave: Represents late depolarization of the ventricles.

S-T segment: Following the QRS is the time at which the entire ventricle is depolarized and roughly corresponds to the plateau phase of the ventricular action potential.

Q-T interval: Represents the time for both ventricular depolarization and repolarization to occur, and therefore roughly estimates the duration of an average ventricular action potential. This interval can range from 0.2 to 0.4 seconds depending upon heart rate.

3.2 Noises in ECG

ECG measurements may be corrupted by many sorts of noise. The ones of primary interest are:

• Power line interference

• Electrode contact noise

• Motion artifacts

• EMG noise

• Instrumentation noise

These artifacts strongly affects the ST segment, degrades the signal quality, frequency resolution, produces large amplitude signals in ECG that can resemble PQRST waveforms and masks tiny features that are important for clinical monitoring and diagnosis. Cancelation of these artifacts in ECG signals is an important task for better diagnosis.

3.2.1 Power line interference

Power line interference occurs through two mechanisms: capacitive and inductive coupling. Capacitive coupling refers to the transfer of energy between two circuits by means of a coupling capacitance present between the two circuits. The value of the coupling capacitance decreases with increasing separation of the circuits. Inductive coupling on the other hand is caused by mutual inductance between two conductors. When current flows through wires it produces a magnetic flux, which can induce a current in adjacent circuits. The geometry of the conductors as well as the separation between them determines the value of the mutual inductance, and hence the degree of the inductive coupling. Typically, capacitive coupling is responsible for high frequency noise while inductive coupling introduces low frequency noise. For this reason inductive coupling is the dominant mechanism of power line interference in electro cardiology. To limit the amount of power line interference, electrodes should be applied properly, that there are no loose wires, and all components have adequate shielding. The Power line interference has frequency of 60 Hz or 50 Hz depending on the power supply.

3.2.2 Electrode contact noise

Electrode contact noise is caused by variations in the position of the heart with respect to the electrodes and changes in the propagation medium between the heart and the electrodes. This causes sudden changes in the amplitude of the ECG signal, as well as low frequency baseline shifts. In addition, poor conductivity between the electrodes and the skin reduces the amplitude of the ECG signal and increases the probability of disturbances (by reducing SNR).

The underlying mechanism resulting in these baseline disturbances is electrode-skin impedance variation. The larger the electrode-skin impedance, the smaller the relative impedance change needed to cause a major shift in the baseline of the ECG signal. If the skin impedance is extraordinarily high, it may be impossible to detect the signal features reliably in the presence of body movement. Sudden changes in the skin-electrode impedance induce sharp baseline transients which decay exponentially to the baseline value. This transition may occur only once or rapidly several times in succession. Characteristics of this noise signal include the amplitude of the initial transition and the time constant of the decay.

3.2.3 Motion artifacts

Motion artifacts are baseline changes caused by electrode motion. The usual causes of motion artifacts are vibrations, movement, or respiration of the subject. The peak amplitude and duration of the artifacts are random variables which depend on the variety of unknowns such as the electrode properties, electrolyte properties (if one is used between the electrode and skin), skin impedance, and the movement of the patient. In this ECG signal, the baseline drift occurs at an unusually low frequency (approximately less than 1Hz).

3.2.4 Electromyography noise

Electromyography noise is caused by the contraction of other muscles besides the heart. When other muscles in the vicinity of the electrodes contract, they generate depolarization and repolarization waves that can also be picked up by the ECG. The extent of the crosstalk depends on the amount of muscular contraction (subject movement), and the quality of the probes. It is well established that the amplitude of the Electromyography signal is stochastic (random) in nature and can be reasonably modeled by a Gaussian distribution function.

The mean of the noise can be assumed to be zero; however, the variance is dependent on the environmental variables and will change depending on the conditions. Certain studies have shown that the standard deviation of the noise is typically 10% of the peak-to-peak ECG amplitude. While the actual statistical model is unknown, it should be noted that the electrical activity of muscles during periods of contraction can generate surface potentials comparable to those from the heart and could completely drown out the desired signal. The frequency of this EMG noise is in between 100-500 Hz.

3.2.5 ECG database

The laboratories at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Centre) and at Massachusetts Institute of Technology (MIT) have supported the research in arrhythmia analysis and related subjects by creating a database. One of the first major products of their effort was the Massachusetts Institute of Technology Beth Israel Hospital (MIT-BIH) database. This database was completed and began distributing in 1980. The database was the first generally available set of standard test material for evaluation of arrhythmia detectors and has been used for that purpose as well as for basic research into cardiac dynamics at more than 500 sites worldwide [34].

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings. These are obtained from 47 subjects collected by from a mixed population of inpatients (about 60%) and outpatients (about 40%) studied by the BIH Arrhythmia Laboratory. The subjects were taken from, 25 men aged 32 to 89 years and 22 women aged 23 to 89 years. About half (25 of 48 complete records and reference annotation files for all 48 records) of this database has been freely available in Physio Net's inception in September 1999 [35]. The 23 remaining signal files, which had been available only on the MIT-BIH Arrhythmia Database CD-ROM, were posted in February 2005 [36]. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range.

3.3 ECG noise reduction algorithms

All the algorithms which are implemented in this thesis for ECG enhancement purpose are described here. For noise reduction purpose, the window-based FIR filtering, adaptive filtering and wavelet filter bank based denoising are used.

3.3.1 FIR filtering

Digital filters are classified either as Finite Impulse Response (FIR) filters or Infinite Impulse response (IIR) filters, depending on the form of unit pulse response of the system. In the FIR system, the impulse response is of finite duration where as in the IIR system, the impulse response is of infinite duration. IIR filters are usually implemented using structures having feedback, that's why the present response of IIR filter is a function of present and past values of the excitation as well as the past value of the response. But the response of the FIR filter usually implemented using structures having no feedback so the response depends only on the present and past values of the input only [29]. The design of FIR filters is preferred due to the following advantages:

• Exact linear phase

• Always stable

• Design methods are linear

• Can be realized efficiently in hardware

• Filter start-up transients have finite duration

3.3.2 Design techniques of FIR filters

The FIR filter is implemented in a non-recursive way which guarantees a stable filter. FIR filter design mainly consists of two parts

i. Approximation part

ii. Realization part

In the approximation stage, the specifications of the filters are taken and a transfer function is generated. In approximation, first an ideal frequency response is taken of length *N* (*N* represents the order of the FIR filter). Then a method or algorithm is selected for the implementation of the filter transfer function. In the realization part, a structure is chosen to implement the transfer function i.e. in the form of circuit diagram or a program.

There are essentially three well-known methods for FIR filter design namely:

i. The window method

ii. The frequency sampling technique

iii. Fourier series method

In our work, we have used the window method of FIR filter design for noise reduction. The window method of filter design is discussed in the following section.

3.3.3 The Window Based FIR Filter Design

In this method, we start with the desired frequency response specification $H(\omega)$ and the corresponding unit sample response $h(n)$ is determined using inverse Fourier transform. The relation between $H(\omega)$ and $h(n)$ is as follows:

$$\mathrm{H}\,(\omega) = \sum_{i=0}^{\infty} h(n)e^{-j\omega n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

where

$$\mathrm{h(n)}=\int_{-\pi}^{\pi} H(\omega)e^{j\omega n}\, d\omega \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

The impulse response *h*(*n*) obtained from the Eq. 3.2 is of infinite duration. So, it is truncated at some point, say n = *M* - 1 to yield an FIR filter of length *M* (i.e. 0 to *M*-1). This truncation of *h(n)* to length *M* - 1 is done by multiplying *h(n)* with a window. Here the design is explained by considering the "rectangular window", defined as

$$W(n)=\begin{cases}1 & n = 0,1,2 \ldots\ldots\ldots .M-1 \\ 0 & otherwise\end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3.3)$$

Thus, the impulse response of the FIR filter becomes

$$P(n)=h(n)*w(n)$$

$$=\begin{cases}h(n) & n = 0,1,2 \ldots\ldots .M-1 \\ 0 & otherwise\end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4)$$

Now, the multiplication of the window function *w*(*n*) with *h*(*n*) is equivalent to convolution of *H(ω)* with *W(ω),* where *W(ω)* is the frequency domain representation (Fourier transform) of the window function i.e.

$$W(\omega) = \sum_{i=0}^{\infty} w(n)e^{-j\omega n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.5)$$

Thus, the convolution of *H(ω)* with *W(ω)* yields the frequency response of the truncated FIR Filter *H(ω).*

$$H(\omega) = \frac{1}{2\pi}\int_{-\pi}^{\pi} H(\vartheta)W(\omega-\vartheta)d\vartheta \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.... (3.6)$$

The frequency response can also be obtained by Fourier transform of h(n), given in the following relation

$$H(\omega) = \sum_{i=0}^{\infty} h(n)e^{-j\omega n} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.... (3.7)$$

But direct truncation of the Fourier series h(n) to M terms to obtain h(n) is known to introduce ripples in the frequency response characteristic H(ω). It is due to the nonuniform convergence of the Fourier series at a discontinuity. The Oscillatory behavior near the band edge of the filter is called Gibbs phenomenon. Thus, the frequency response obtained using Eq. 3.7 contains ripples in the frequency domain [37].

In order to reduce the ripples, h(n) is multiplied with a window function that contains a taper and decays toward zero gradually instead of abruptly as it occurs in a rectangular window. As multiplication of sequences h(n) and w(n) in time domain is equivalent to convolution of H(ω)and W(ω) in the frequency domain, it has the effect of smoothing H(ω).

The several effects of windowing the Fourier coefficients on the frequency response of the filter are as follows [38]:

• A major effect is the discontinuities in $H(\omega)$.

• The width of the transition bands depends on the width of the main lobe of the frequency response of the window function $w(n)$ i.e. $W(\omega)$.

• Since, the filter frequency response is obtained via a convolution relation, it is c lear that the resulting filters are never optimal in any sense.

• As M (the length of the window function) increases, the main lobe width of $W(\omega)$ is reduced which reduces the width of the transition band, but this also introduces more ripple in the frequency response.

• The window function eliminates the ringing effects at the band edge and does result in lower side lobes at the expense of an increase in the width of the transition band of the filter

The major advantages of using window method are their relative simplicity and ease of use as compared to other methods. The fact that well defined equations are often available for calculating the window coefficients has made this method successful.

There are following problems in filter design using window method [39]:

• This method is applicable only if $H(\omega)$ is absolutely integrable, i.e. only if Eq. 3.2 can be evaluated. When $H(\omega)$ is complicated or cannot easily be put into a closed form mathematical expression, evaluation of $h(n)$ becomes difficult.

• The use of windows offers very little design flexibility, e.g. in low-pass filter design, generally the pass band edge frequency cannot be specified exactly, since the window smears the discontinuity in frequency. Thus, the ideal LPF with cut-off frequency fc, is smeared by the window to give a frequency response with pass band response with pass band cut off frequency $f1$ and stop band cut-off frequency $f2$.

• Window method is basically useful for design of prototype filters like low pass, high pass, band pass, etc. This makes its applications very limited.

3.4 Adaptive filtering

Adaptive filtering involves the change of filter parameters (coefficients) over time. It adapts to the change in signal characteristics in order to minimize the error. It finds its application in adaptive noise cancellation, system identification, frequency tracking and channel equalization [41]. Fig. 3.5 shows the general structure of an adaptive filter.

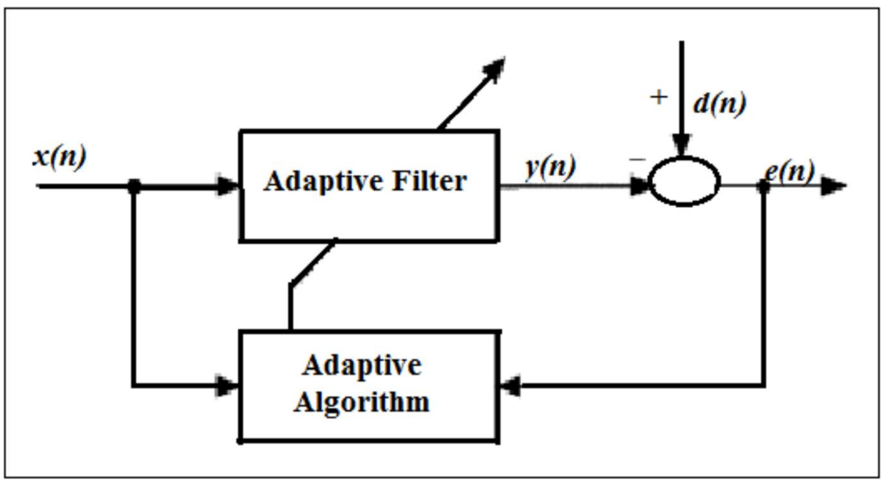


Figure 3.5: Adaptive filter structure

In Figure 3.5, *x(n)* denotes the input signal. The vector representation of *x(n)* is given in Eq. 3.12. This input signal is corrupted with noises. In other words, it is the sum of desired signal *d(n)* and noise *v(n)*, as mentioned in Eq. (3.13).

The input signal vector is *x(n)* which is given by

$$X(n)=[x(n), x\ (n-1).,\ldots\ldots x(n-N-1)]^{T}\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ldots\ldots..(3.8)$$

$$X(n)=d(n)+\vartheta(n)$$

The adaptive filter has a Finite Impulse Response (FIR) structure. For such structures, the impulse response is equal to the filter coefficients. The coefficients for a filter of order N are defined as

$$W(n)= [w (0), w (1), \ldots\ldots\ldots\ldots\ldots\ w(n-1)]^{T} \ldots\ldots\ldots\ldots\ldots\ldots \quad (3.9)$$

The output of the adaptive filter is *y(n)* which is given by

$$Y(n)=w(n)^{T} *x(n)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.10)$$

The error signal or cost function is the difference between the desired and the estimated signal

$$e(n)=d(n)-y(n)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.11)$$

Moreover, the variable filter updates the filter coefficients at every time instant

$$W(n+1) =w(n)+\Delta w(n)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.12)$$

where $\Delta w(n)$ is a correction factor for the filter coefficients. The adaptive algorithm generates this correction factor based on the input and error signals [42].

3.4.1 Adaptive Algorithms

In adaptive filters, the weight vectors are updated by an adaptive algorithm to minimize the cost function. The algorithms used by us for noise reduction in ECG in this thesis are least mean square (LMS),

LMS algorithm

It is a stochastic gradient descent method in which the filter weights are only adapted based on the error at the current time. According to this LMS algorithm the updated weight is given by

$$W(n+1) =W(n)+2*\mu*x(n)*e(n)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.13)$$

where μ is the step size

.

DLMS algorithm

In the DLMS algorithm, only one type of delay is considered. On the other hand, it is known that to implement fast adaptive filters working in real time, it is necessary to introduce different types of delay to allow a flexible architecture. For instance, in the pipelined architecture, there are different types of delay at the bit level. This situation gives rise to the following question: is it possible for the LMS algorithm with different types of delays to offer a good trade-off between performance in convergence and error and sampling rate? This work tries to give some answers to this problem.

The generalized delay LMS algorithm (DLMS) is described by the following equations:

$$Y(n)= X^T *W (n-1-D_1) \qquad (3.14)$$

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

$$W(n)= w(n-1-D_2) +\mu e(n-D_3)*x(n-D_4) \qquad (3.15)$$

Where W(n)X(n), d(n), and y(n) are respectively the coefficient vector of the filter of order N, the input vector, the desired signal, and the output signal of the filter. D1, D2, D3, and D4 are four different types of delays and μ is the constant step of the adaptation. To simplify the notation, we define the delay vector D= [D1, D2, D3, D4]. Numerical simulations have been done in order to analyze the behavior of the GDLMS algorithm. Simulations results show that there is no convergence for non-zero D2. When D2= 0, the convergence speed seems not to depend simultaneously on D1 and (D3, D4). Some typical results are shown in tables 1-3, for different values of μ and where no indicates the number of cycles to insure convergence.

CHAPTER 4

Results and Discussion

4.1 ECG waveform

The main ECG signal or waveform is shown in Figure 4.1. The ECG waveform is obtained from MATLAB Simulink software. This signal is getting by using the following instruction

x=ecg (500);

The MATLAB Simulink software automatically generate this ECG signal when above instruction is running.

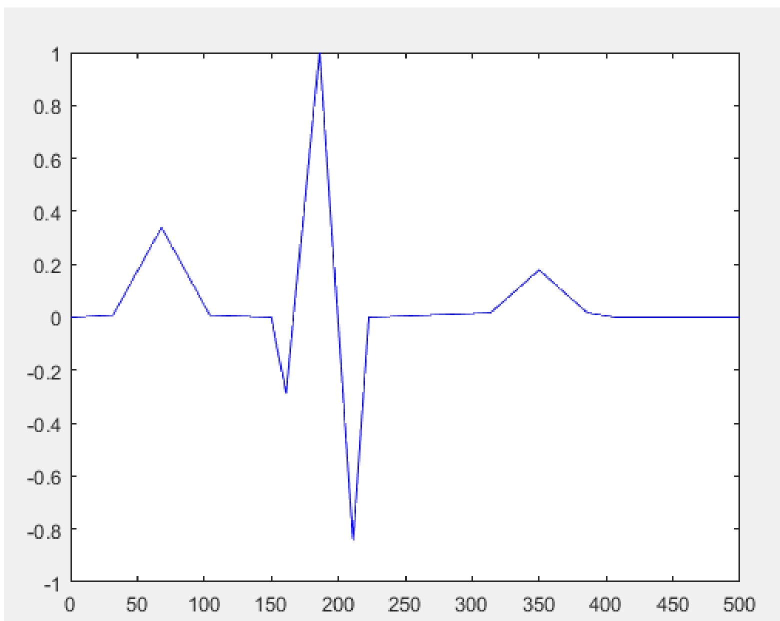


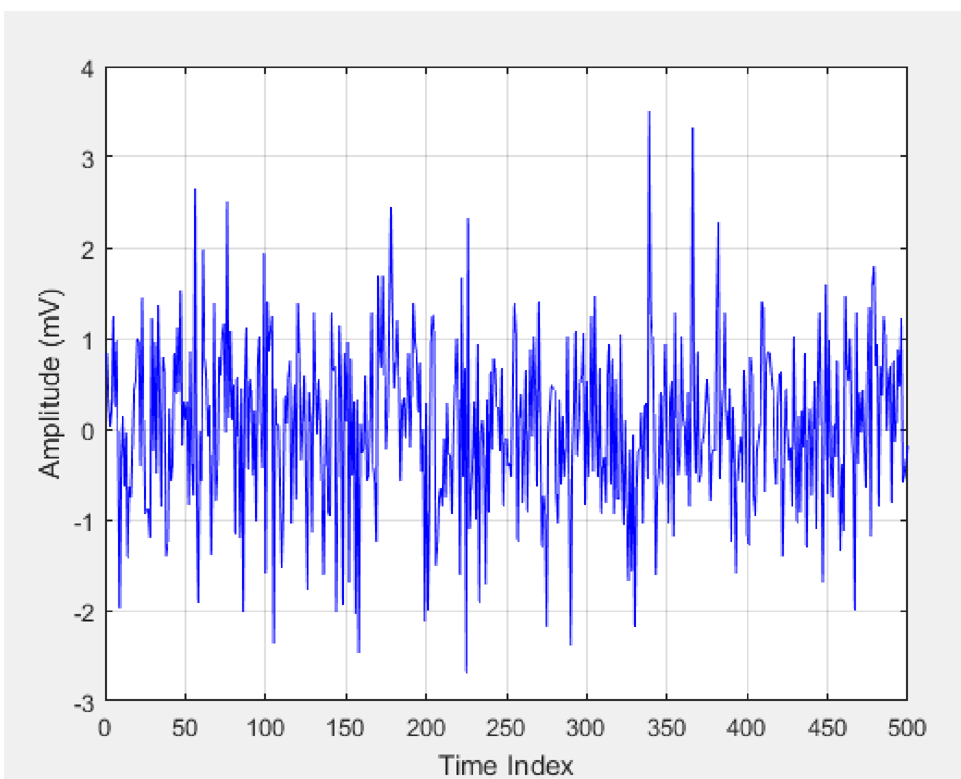
Figure 4.1: ECG signal

4.2 Generation of noise

The artifacts in ECG can be categorized according to their frequency content. The low frequency noise (electrode contact noise and motion artifact) has frequency less than 1 Hz, high frequency noise (EMG noise) whose frequency is more than 100 Hz and power line interference of frequency 50 Hz or 60 Hz (depending on the supply). These noises are generated in MATLAB based on their frequency content.

4.2.1 Generation of high frequency noise

High frequency noise is generated by multiplying sine wave of 50 Hz frequency with a random signal. The generated high frequency noise is shown in Figure 4.2.The random signal is obtained from MATLAB building function.



.

Figure 4.2: High frequency noise.

4.2.2 Generation of power line interference

Here the 50 Hz power supply is considered. So, a sine wave of 50 Hz amplitude was taken to represent the power line interference. The resulted power line interference is shown in Figure 4.3. Such type of noise is originated into ECG signal due to the fault of power line connection. By using the MATLAB Simulink software this noise can be achieved.

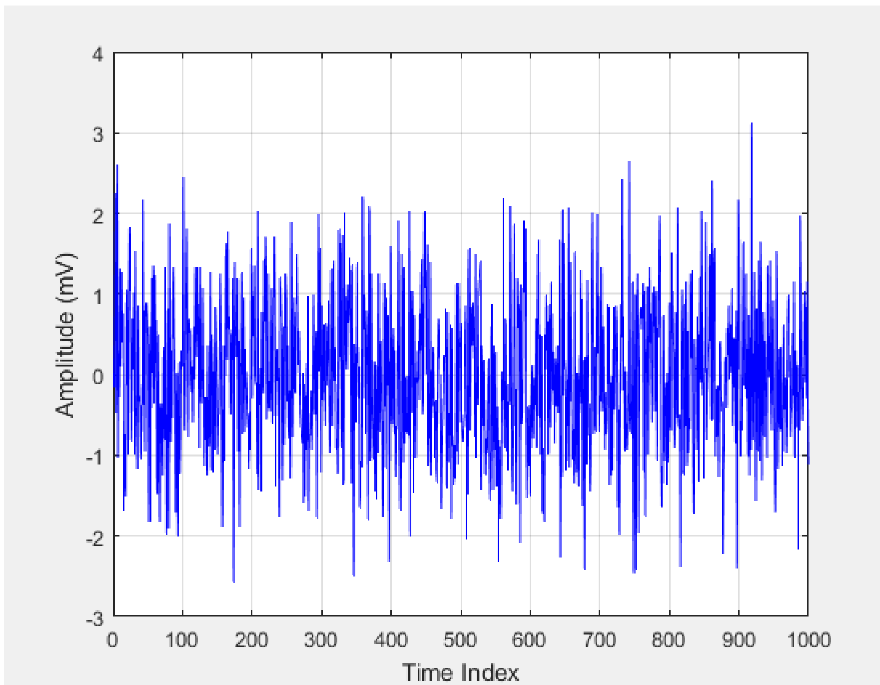


Figure 4.3: Power line interference.

4.2.3 Addition of noise in ECG

The noise signals generated are added with the ECG signal to get the corrupted ECG. Figure 4.4 shows the corrupted ECG. The contaminated ECG can be constructed by using MATLAB software. The added signal is the mixer of noise and original ecg signal.

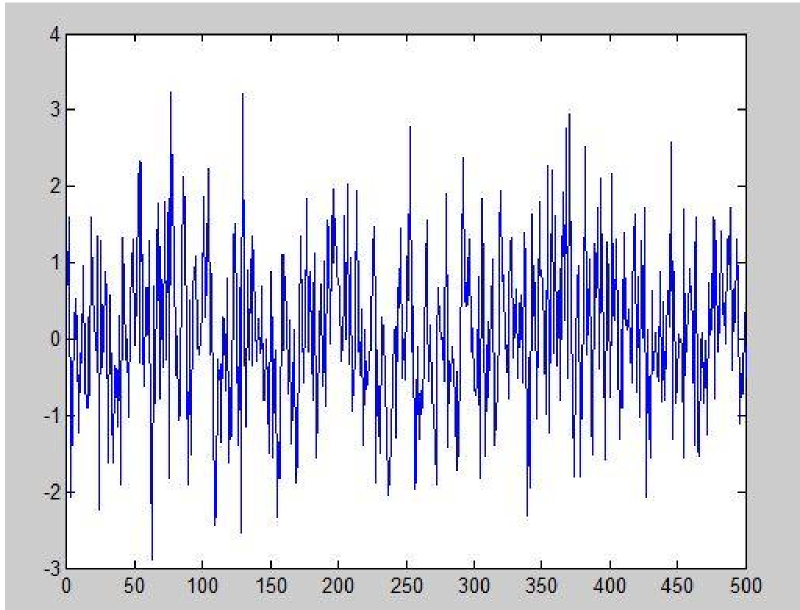


Figure 4.4: Corrupted ECG signal.

4.3 Results of adaptive filtering

The corrupted signal shown in Figure 4.4 is passed through the adaptive filters. Figure 4.5, 4.6, 4.7, 4.8 shows the filtered output of the adaptive filters using LMS, DLMS algorithms respectively.

The reduction of random noise which originates from motion artifacts, speed of blood etc. results is shown below in the Figure 4.5 & 4.6.

From the resultant output we can see that the reconstructed ECG signal is looking like to original signal. The filter co-efficient value is so much closer to each other sometimes they are overlapping. The filter co-efficient indicates the performance of the filter. So the filtered output is directly connected to the filter co-efficient.

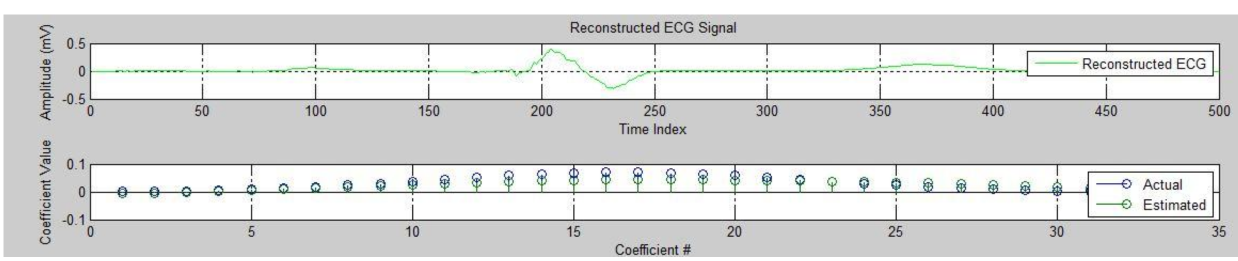


Figure 4.5: ECG signal after passing through LMS based filter (motion artifacts)

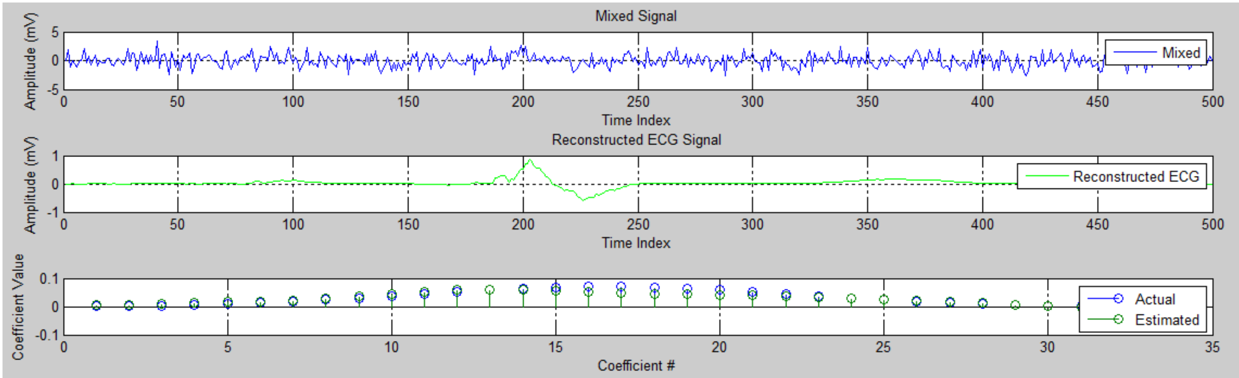


Figure 4.6: ECG signal after passing DLMS based filter (motion artifacts)

The reduction of additive white Gaussian noise which is originates from power line interference result is shown below in the Figure: 4.7 & 4.8.

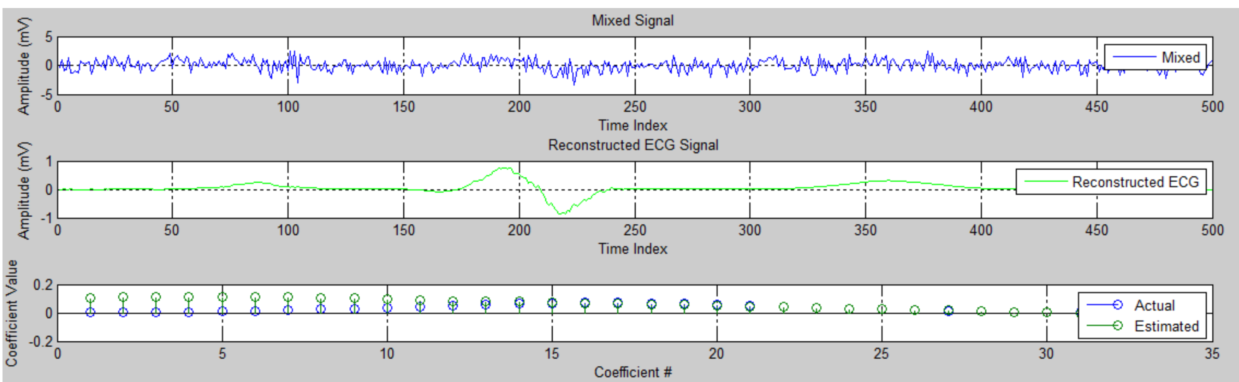


Figure 4.7: ECG signal after passing LMS based filter (power line)

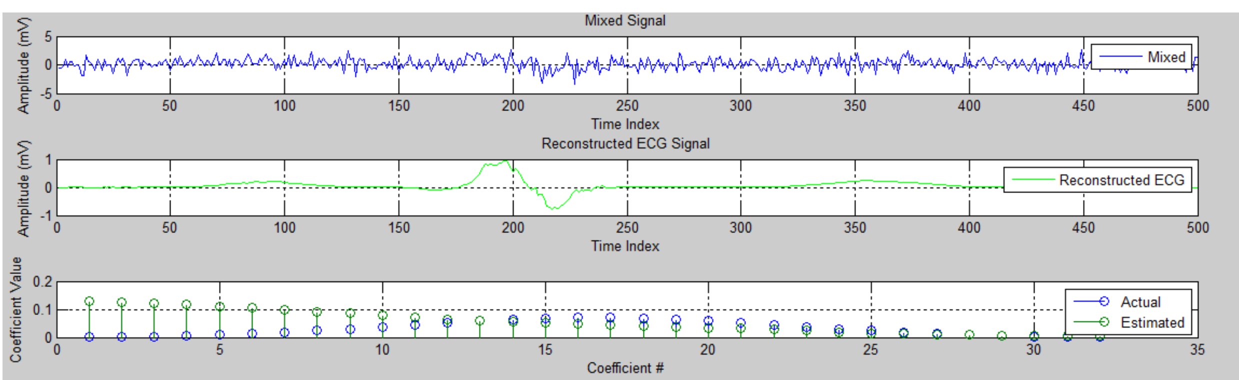


Figure 4.8: ECG signal after passing DLMS based filter (power line)

Table 4.1: The comparison table of step size during de noising

Methods	**Noise name**	**The value of step size μ**
LMS	Random noise	0.003
	Additive white Gaussian noise	0.0082
DLMS	Random noise	0.0085
	Additive white Gaussian noise	0.0072

For LMS method random noise use the step size 0.003. This value is more suitable for convergence rate and steady state error. And additive white gaussian noise use another step size. They use another step size because FIR window method prefers different step size for different algorithm. Same phenomenon is also occurred for DLMS method.

CHAPTER 5

Conclusion and Future Scope

This chapter focuses on the advantages and limitations of all the algorithms used for ECG enhancement. The scopes of future research work in this domain are also discussed.

5.1 Conclusion

This thesis throws light on the basics of electrocardiogram, artifacts corrupting the ECG signal and ECG enhancement using different algorithms. The thesis begins with the review of some popular work in the field of ECG signal processing. The physiology of heart, heart beat generation, morphology of electrocardiogram are elaborately discussed. Different types of noises that affect the ECG and their origins are also described. For the simulations, the ECG signals are taken from the MATLAB data base. The later part of the thesis deals with all the filtering algorithms that are used and the simulation results.

The filtering algorithms used in this thesis are window based FIR filtering, adaptive filtering and LMS, and DLMS algorithm. The advantage and limitations of all the used methods are discussed below.

• The first algorithm is the window based FIR filters, The performance of FIR based filter is better than the rest filters as the digital filter has sharp attenuation and pulsation present in the stop band. The phase response of FIR filter is linear and the filter is also stable.

• The second algorithm analyses the performance of different adaptive filters for ECG noise reduction. In LMS based adaptive filter, the step size is smaller than DLMS algorithm and hence the convergence is slower but the accuracy of the desired signal is higher. When the step size is higher the convergence is fast but the accuracy is slower. So for different types of noise the value of step size is determined separately. The residue of the raw signal and the approximate noise is obtained to get noise free ECG signal. The proposed method removes noise from the ECG signal without any distortion of the ECG signal features.

5.2 Direction of future research

In the present work, the FIR technique depended LMS and DLMS algorithm based adaptive filters remove the high frequency, power line interference and low frequency noises. The future developments to this work can be made as follows:

- Implementation of LMS based de-noising for the removal of noise originates from base line wander.
- Use of other adaptive methods and algorithms for ECG de-noising.
- Application of blind adaptive filtering for ECG enhancement.
- Real time application of implemented algorithms.

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