Implementation of Digital Filters for the Removal of Artifacts from Electrocardiogram

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Abstract— **In this paper various digital filters based algorithms that can be applied to ECG signal in order to remove artifacts from them are presented. Noises that commonly disturb the basic electrocardiogram 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. Different types of adaptive and non-adaptive digital filters have been proposed to remove these noises. In this paper, window based FIR filters, adaptive filters and wavelet filter banks are applied to remove the artifacts. Performances of the filters are compared based on PSNR values.**

Index Terms— **ECG denoising, FIR filter, Adaptive filter, Wavelet Decomposition, PSNR.**

I. INTRODUCTION

The electrocardiogram (ECG) is a graphical representa-tion of the cardiac activity and it is widely used for the diagnosis of heart diseases [1]. In clinical environment during acquisition, the ECG signal encounters various types of artifacts. The predominant artifacts present in the ECG signal are Power-line Interference (PLI), Baseline Wander (BW), Muscle Artifacts (MA) and Motion Artifacts (EM). In this paper Power-line Interference is considered for PSNR simulations.

Power-line interference (PLI) is a significant source of noise during bio-potential measurements. It degrades the signal quality. In most existing PLI suppression methods, it is assumed that 1) the PLI is already present in the input ECG signal, 2) the number of harmonics is known (usually a single sinusoid), and 3) the frequencies of the narrow band harmonics or the statistics of them are known. But these assumptions are often unrealistic in real-world applications.It is essential to reduce disturbances in ECG signal and improve the accuracy and reliability for better diagnosis[1].

Different methods have been implemented to remove the artifacts from noisy ECG signal. The basic method is to pass the signal through static filters such as IIR, FIR and notch filters. In some cases these static filters also remove some important frequency components in the vicinity of cut off frequency. The static filters have fixed filter coefficients and it is very difficult to reduce the instrumentation noise with fixed filter coefficients, because the time varying behavior of this noise is not exactly known. To overcome the limitations of static filters, different adaptive filtering techniques have been developed. Adaptive filtering techniques are used for the processing and analysis of the ECG signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Some examples of dynamic filters are adaptive Kalman filter, wiener filter, modified extended Kalman filter etc. In this paper, various filters have been implemented for removal of artifacts in ECG. Their performances are also compared based on the PSNR values.

This paper is organized as follow: Section I gives the introduction of the ECG signal and power-line interference noise that affects the ECG. Section II explains ECG Denoising using non adaptive filter algorithms. Section III describes Denoising using adaptive filter algorithms with their equations of the related work. This section also explains the basic adaptive filter structure used for primitive LMS algorithm, which forms a base for all the other improved algorithms. Section IV explains the Wavelet based Denoising algorithms. Section V shows the simulation results and performance of the proposed techniques and at last section VI concludes the paper and followed by the references.

II. ECG DENOISING ALGORITHMS

For denoising purpose, the window based FIR filtering, adaptive filtering and wavelet filter bank based denoising are used.

A. FIR FILTERING

Digital filters are classified either as Finite Impulse Response (FIR) filters or Infinite Impulse response (IIR) filters, depending on the impulse 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 filter structures are having feedback, that’s why the present response of IIR

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filter is a function of present and past values of the excitation as well as the past value of the output [5]. But the response of the FIR filter structures having no feedback so the response depends only on the present and past values of the input only.FIR filters are always stable, Exact linear phase, Can be realized efficiently in hardware. Due to the above advantages the design of FIR filters is preferred .

B. The Window Based FIR Filter Design

In this method, we start with the desired frequency response $H_d(\omega)$ and the corresponding unit sample response $h_d(n)$ is determined using inverse Fourier transform. The relation between $H_d(\omega)$ and $h_d(n)$ is as follows[7] :

$$H_d(\omega) = \sum_{n=0}^{\infty} h_d(n) e^{-j\omega n} \quad (1)$$

Where $h_d(n) = \int_{-\pi}^{\pi} H_d(\omega) e^{j\omega n} \, d\omega$ (2)

The impulse response $h_d(n)$ obtained from the Eq.(2) is of infinite duration. So, it is truncated at some point, say n = N - 1 to yield an FIR filter of length N (i.e. 0 to N-1). This truncation of $h_d(n)$ to length N - 1 is done by multiplying $h_d(n)$ with an window . Here the design is explained by considering the “rectangular window”, defined as

$$w(n) = \begin{cases} 1 & n = 0,1,2.......N-1 \\ 0 & otherwise \end{cases} \quad (3)$$

Thus, the impulse response of the FIR filter becomes

$$h(n) = h_d(n)\, w(n) \quad (4)$$

$$h(n) = \begin{cases} h_d(n) & n = 0,1,2.......N-1 \\ 0 & otherwise \end{cases} \quad (5)$$

Design flexibility is very less and window method is basically useful for design of prototype filters like low pass, high pass, band pass, etc. This makes its applications very limited. Due to these reasons Adaptive filters are proposed.

III ADAPTIVE FILTERING AND ALGORITHMS

In this chapter we investigate performance of Adaptive filter and adaptive noise cancellation, system identification, frequency tracking and channel equalization[8]. Adaptive filtering involves the change of filter filter coefficients over time. It adapts to the change in signal characteristics in order to minimize the error. The general structure of an adaptive filter is shown in figure1.

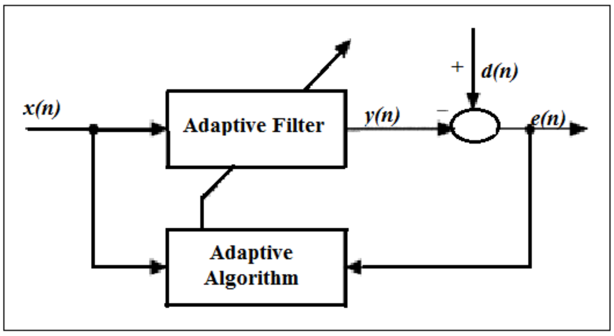

Figure 1: Adaptive filter structure

In figure1. $x(n)$ denotes the input signal. The vector representation of $x(n)$ is given by

$$x(n) = [x(n), x(n-1),.........x(n-N-1)]^T \quad (6)$$

This input signal is corrupted with noises. In other words, it is the sum of desired signal $d(n)$ and noise $v(n)$ i.e.

$$x(n) = d(n) + v(n) \quad (7)$$

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

$$w(n) = [w_n(0), w_n(1),......w_n(N-1)]^T \quad (8)$$

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

$$y(n) = w(n)^T x(n) \quad (9)$$

The error signal is the difference between the desired and the estimated signal

$$e(n) = d(n) - y(n) \quad (10)$$

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

$$w(n+1) = w(n) + \Delta w(n) \quad (11)$$

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.

In adaptive filters, the weight vectors are updated by an adaptive algorithm to minimize the error function. The algorithms used for noise reduction in ECG in this thesis are least mean square (LMS), Normalized least mean square (NLMS), Sign data least mean square (SDLMS),Sign error least mean square (SELMS) and Sign-Sign least mean square (SSLMS) algorithms.

A. LMS algorithm

According to this LMS algorithm the updated weight is given by

$$w(n+1) = w(n) + 2.\mu.x(n).e(n) \quad (12)$$

Where μ is the step size.

B. NLMS algorithm

The NLMS algorithm is a modified form of the standard LMS algorithm. The NLMS algorithm updates the coefficients of an adaptive filter by using the equation

$$w(n+1) = w(n) + 2.\mu.\frac{x(n)}{\|x(n)\|^2}.e(n) \quad (13)$$

Eq. (13) can be rewritten as

$$w(n+1) = w(n) + 2.\mu(n).x(n).e(n) \quad (14)$$

Where $\mu(n) = \frac{\mu}{\|x(n)\|^2}$

From Eq. (12) and Eq.(14) the NLMS algorithm becomes the same as the standard LMS algorithm except that the NLMS algorithm has a time-varying step size $\mu(n)$. This step size improves the convergence speed of the adaptive filter.

C. SDLMS algorithm

In SDLMS algorithm, the sign function is applied to the input signal vector $x(n)$. This algorithm updates the coefficients of an adaptive filter using the equation.

$$w(n+1) = w(n) + 2.\mu.x(n).\text{sgn}(x(n)).e(n) \quad (15)$$

D. SELMS algorithm

In SELMS, the sign function is applied to the error signal *e(n)*. This algorithm updates the coefficients of an adaptive filter using the equation.

$$w(n+1) = w(n) + 2.\mu.x(n).\text{sgn}(e(n)) \quad (16)$$

E. SSLMS algorithm

Here, the sign function is applied to both $e(n)$ and $x(n)$. This algorithm updates the coefficients of an adaptive filter using the equation

$$w(n+1) = w(n) + 2.\mu.\text{sgn}(x(n)).\text{sgn}(e(n)) \quad (17)$$

VI WAVELET DENOISING

The wavelet transform is similar to the Fourier transform. For the FFT, the basis functions are sines and cosines. For the wavelet transform, the basis functions are more complicated called wavelets, mother wavelets or analyzing wavelets and scaling function. In wavelet analysis, the signal is broken into shifted and scaled versions of the original (or *mother*) wavelet. Wavelet transform is suitable for multiresolution used for the analysis of non-stationary signals such as the ECG signal.

A. Wavelet Transform

If we take the Fourier transform over the whole time axis, we cannot tell at what instant a particular frequency rises. Short-time Fourier transform (STFT) uses a sliding window to find spectrogram, which gives the information of both time and frequency. But the length of window limits the resolution in frequency. To avoid this problem Wavelet transform is a good choice. Wavelet transforms (WT) are based on small wavelets with limited duration. In WT both the time and frequency resolutions vary in time-frequency plane in order to obtain a multiresolution analysis[9].

In wavelet transform, a signal x(t) can be written as

$$x(t) = \sum_k a_{j0,k}\varphi_{j0,k}(t) + \sum_{j=j0}^{\infty}\sum_k b_{j,k}\psi_{j,k}(t) \quad (18)$$

where *a, b* are the coefficients associated with $\varphi_{j,k}(t)$ and $\psi_{j,k}(t)$ respectively, and x(t) belongs to the square integrable subspace $L^2(R)$ is expressed in terms of scaling function $\varphi_{j,k}(t)$ and mother wavelet function $\psi_{j,k}(t)$.Here *j* is the parameter of dilation or the visibility in frequency and *k* is the parameter of the position.The coefficients *a, b* can be using the following equations (19) and (20).

$$a_{j0,k} = \int_{-\infty}^{\infty} x(t)\,\varphi_{j0,k}(t)\,dt \quad (19)$$

$$b_{j,k} = \int_{-\infty}^{\infty} x(t)\,\psi_{j,k}(t)\,dt \quad (20)$$

The scaling function $\varphi_{j,k}(t)$ can be expressed in equation (21)

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j t - k) \quad (21)$$

$\psi_{j,k}(t)$ can also be derived from its shifted version i.e. $\psi_{j,k}(2t)$. The expression of $\varphi_{j,k}(t)$ in terms of $\varphi_{j,k}(2t)$ will be

$$\varphi(t) = \sum_n h_\varphi(n)\sqrt{2}\,\varphi(2t-n)$$

(22)

In Eq. (22) n is the shifting parameter and $h_\varphi(n)$ are the coefficients.

The mother wavelet function $\psi_{j,k}(t)$ is expressed in equation (23) i.e.

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^{j}t-k) \quad (23)$$

$\psi_{j,k}(t)$ can also be written using shifted version $\varphi_{j,k}(t)$ i.e. $\varphi_{j,k}(2t)$. The expression of $\psi_{j,k}(t)$ will be $\psi(t) = \sum_{n} h_{\psi}(n)\sqrt{2}\varphi(2t-n)$ (24)

In Eq. (24) n is the shifting parameter and $h_{\psi}(n)$ are the coefficients.

B. Discrete Wavelet Transform

Discrete wavelet transform (DWT) decomposes the signal into mutually orthogonal set of wavelets. The scaling function $\varphi_{j,k}(n)$ and the mother wavelet function $\psi_{j,k}(n)$ in discrete domain are represented in equations (25) and (26).

$$\varphi_{j,n}(n) = 2^{j/2}\varphi(2^{j}n-k) \quad (25)$$

$$\psi_{j,n}(n) = 2^{j/2}\psi(2^{j}n-k) \quad (26)$$

The DWT of an discrete signal *x(n)* of length N-1 is given by

$$x(n) = \sum_{k} W_{\varphi}(j_0,k)\,\varphi_{j0,k}(n) + \sum_{j=j0}^{\infty}\sum_{k} W_{\psi}(j_0,k)\psi_{j,k}(n)$$

Here $W_{\varphi}(j_0,k)$ and $W_{\psi}(j_0,k)$ are called the wavelet coefficients.

$\varphi_{j,k}(n)$ and $\psi_{j,k}(n)$ are orthogonal to each other. Hence we can simply take the inner product to obtain the wavelet coefficients.

$$W_{\varphi}(j_0,k) = \frac{1}{\sqrt{M}}\sum_{n} x(n)\varphi_{j0,k}[n] \quad (27)$$

$$W_{\psi}(j,k) = \frac{1}{\sqrt{M}}\sum_{n} x(n)\psi_{j0,k}[n] \qquad j \geq j_0 \quad (28)$$

The coefficients $W_{\varphi}(j_0,k)$ in equation (27) are called the approximation coefficients and the coefficients $W_{\psi}(j_0,k)$ in equation (28)are called the detailed coefficient.The DWT can be realized in terms of high pass and low pass filters. The output of the low pass filter gives the approximation coefficients and the output of the high pass filter gives the detailed coefficients.

To get the filter coefficients $W_{\varphi}(j_0,k)$ and $W_{\psi}(j_0,k)$ can be rewritten as

$$W_{\varphi}(j,k) = \sum_{n} h_{\varphi}(n-2k)W_{\varphi}(j+1,m) \quad (29)$$

$$W_{\psi}(j,k) = \sum_{m} h_{\psi}(m-2k)W_{\psi}(j+1,m) \quad (30)$$

h_{φ} and h_{ψ} are the low pass filter and high pass filter coefficients in equations (29)and (30).

C. Wavelet Decomposition

The DWT decomposes the signal into approximate and detail information. Thus, it helps in analyzing the signal at different frequency bands with different resolutions[10].

1. Single stage wavelet filtering

Single stage wavelet filtering process is the most basic level. In this the original signal *x(n)* is passed through two complementary filters and emerges as two signals as shown in figure 2.

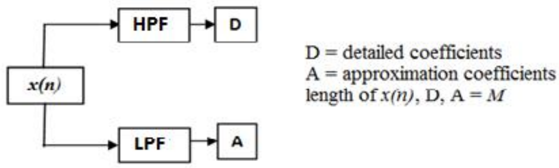

Figure 2: Single stage wavelet filtering

The original signal *x(n)* consists of *M* samples of data. If we apply single stage wavelet filter the resulting approximation and detail coefficients are each of length *M*, for a total of *2M*. There exists an alternative method to perform the decomposition using wavelets. By down sampling A and D to half of their lengths i.e. *M/2,* the total length of resulting signal can be maintained. The final output signals after down sampling are denoted as cA and cD. It is shown in figure 3.

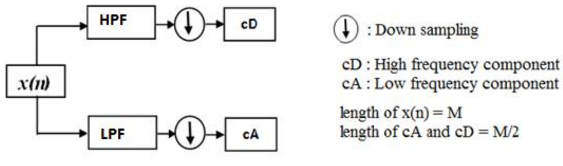

Figure3: Single stage wavelet filtering with down sampling

2 . Multistage wavelet filtering

In this wavelet decomposition process one signal is broken down into many lower resolution components. This is called the wavelet decomposition tree.

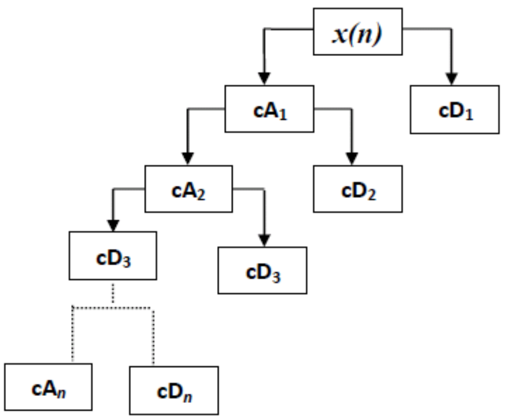

Figure 4:.Multistage Wavelet Decomposition tree.

Multistage wavelet filtering analysis process is iterative, theoretically it can be continued till infinite levels. Ideally the decomposition can be done only until the individual details consist of a single sample. In practice, a suitable number of decomposition levels based on the nature and frequency component of the signal.

3. *Wavelet Reconstruction*

After decomposition, the task is to again reconstruct the original signal without loss of important information. This process is called *reconstruction*, or *synthesis*. The synthesis is done mathematically by using the inverse discrete wavelet transform (IDWT).

In wavelet analysis, filtering and followed by down sampling are involved. But the wavelet reconstruction process consists of up sampling followed by filtering. Up sampling is the process of lengthening a signal component by inserting zeros between samples.

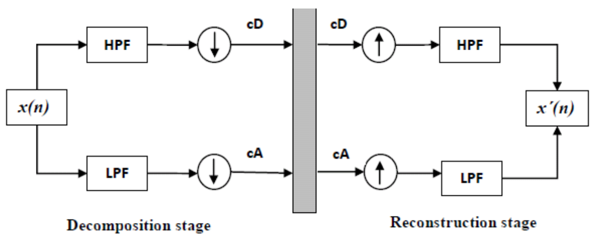

Figure 5: Single stage decomposition and reconstruction.

We combine cA and cD by IDWT to get the reconstructed original signal. For multiple level reconstruction, the single stage reconstruction technique is iterated to reassemble the original signal.

D. *ECG Denoising Using Wavelet Transform*

In this method, the corrupted ECG signal *x(n)* is denoised by taking the DWT of raw and noisy ECG signal. A family of the mother wavelet is available having the energy spectrum concentrated around the low frequencies like the ECG signal as well as better resembling the QRS complex of the ECG signal. We have used *symlet* wavelet, which resembles the ECG wave.

In discrete wavelet transform (DWT), the low and high frequency components in *x(n)* is analyzed by passing it through a series of low-pass and high-pass filters with different cut-off frequencies. This process results in a set of approximate coefficients (cA) and detail coefficients (cD). To remove the power line interference and the high frequency noise, the DWT is computed to level 4 using *symlet8* mother wavelet function and scaling function. Then the approximate coefficients at level 4 (cA4) are set to zero. After that, inverse wavelet transform (IDWT) of the modified coefficients are taken to obtain the approximate noise of the ECG signal. The residue of the raw signal and the approximate noise is obtained to get noise free ECG signal.

V. Simulation Results

All the simulation results are obtained by using MATLAB.The ECG waveform taken from MIT-BIH database, generated noises and the corrupted ECG signal are also shown.

A. *ECG WAVEFORM*

All the simulations shown in the later parts are carried out with data no. 100 of MIT-BIH arrhythmia database. The ECG waveform is shown in figure 6.

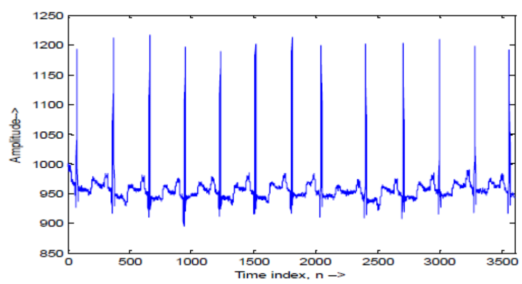

Figure 6: ECG signal

B. *GENERATION OF NOISES*

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.

1. *Generation of Low Frequency Noise (Base Line Wander)*

We generated the baseline drift by adding two sine waves of frequency 0.1 Hz and 0.02 Hz and Triangular wave of 0.05Hz which is shown in figure 7.

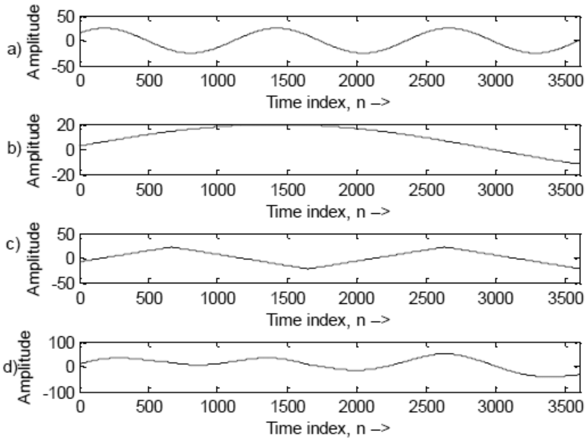

Figure 7: (a) Sine wave of frequency 0.1Hz (b)Sine wave of frequency 0.02Hz (c) Triangular wave of frequency 0.05Hz (d) base line wander.

2. *Generation of High Frequency Noise*

High frequency noise is generated by multiplying sine wave of 150 Hz frequency with a random signal. The generated high frequency noise is shown in figure 8.

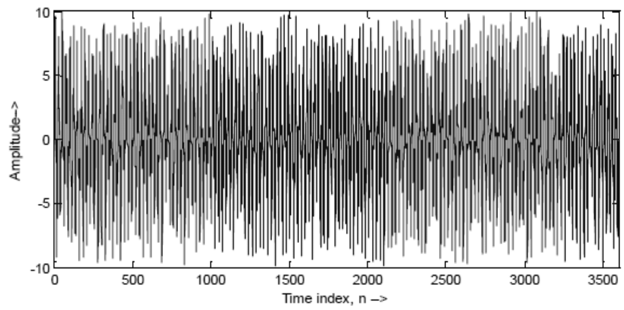

Figure 8: High Frequency Noise.

3. *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 9.

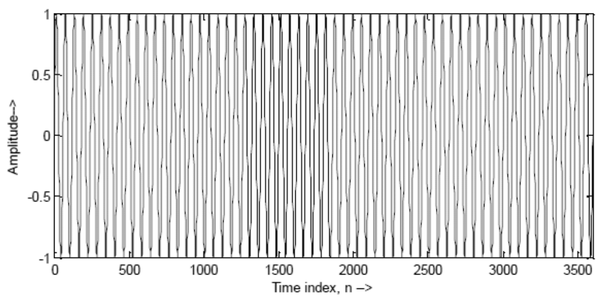

Figure 9: Power line interference

4. *ADDITION OF NOISES TO ECG*

The noise signals generated are added with the ECG signal to get the corrupted ECG. figure. 10 shows the corrupted ECG.

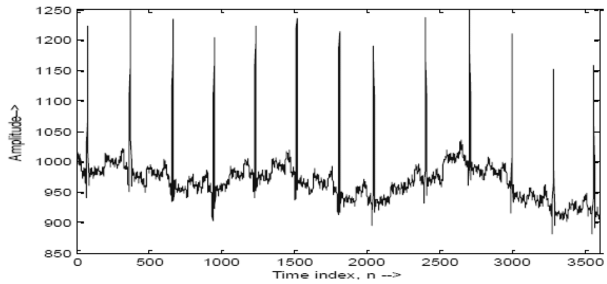

Figure 10: Corrupted ECG Signal

C. *RESULTS OF WINDOW BASED FIR FILTERING*

We designed FIR filters of order 100.Rectangular window based FIR filter gives the response with sharp attenuation and pulsation in the stop band. In the pass band, the filter was found to be stable. The Hamming, Hanning and the Blackman windows do not have a sharp cut-off like the Rectangular window. Using these windows, we designed the high pass filter of cut-off frequency 3 Hz and the low pass filter of cut-off frequency 100Hz. figure. 11, 12, 13, 14 show the filtered ECG signal by passing through the FIR filter based on Rectangular window, Hamming window, Hanning window and Blackman window respectively.

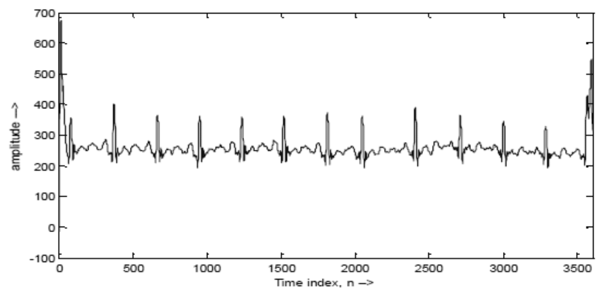

Figure 11: ECG signal after passing through FIR filter with Rectangular Window.

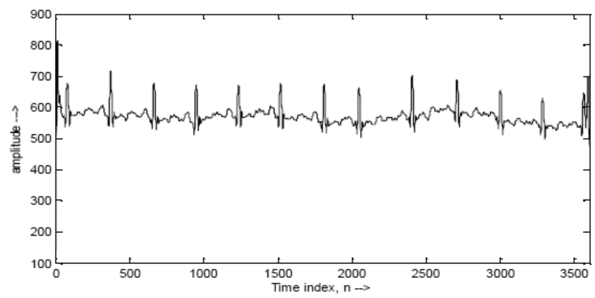

Figure 12: ECG signal after passing through FIR filter with Hamming window

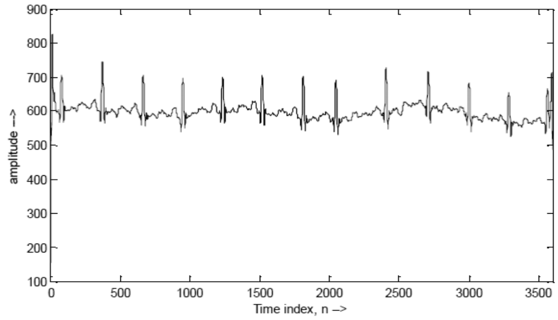

Figure 13: ECG signal after passing through FIR filter with Hanning window

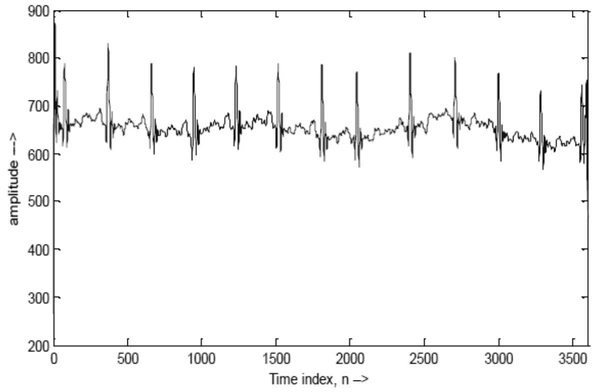

Figure 14: ECG signal after passing through FIR filter with Blackman window.

To evaluate the performance of all these filters PSNR values are calculated which is listed in the Table 1.

TABLE I
PSNR COMPARISION OF WINDOW BASED FIR FILTERS

Window Type	PSNR(dB)
Rectangular	21.13
Hanning	18.65
Hamming	18.90
Blackman	18.00

The Table1. shows the performance of rectangular window based filter is better than the rest window based filters because the rectangular filter has sharp attenuation and pulsation present in the stop band. The phase response of rectangular window based filter is linear and the filter is also stable.

D. RESULTS OF ADAPTIVE FILTERING

The corrupted ECG signal shown in Figure10. is passed through the adaptive filters. Figure. 15, 16, 17,18 and 19 show the filtered output and the error plot of the adaptive filters using LMS, NLMS, SDLMS, SELMS, SSLMS algorithms respectively.

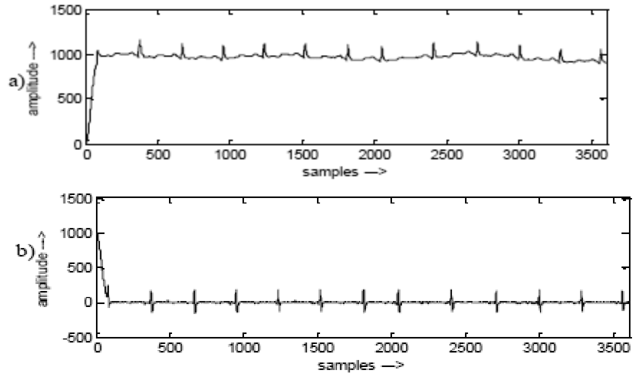

Figure 15: (a) ECG signal after passing through LMS based filter (b) Error plot after passing through LMS based adaptive filter

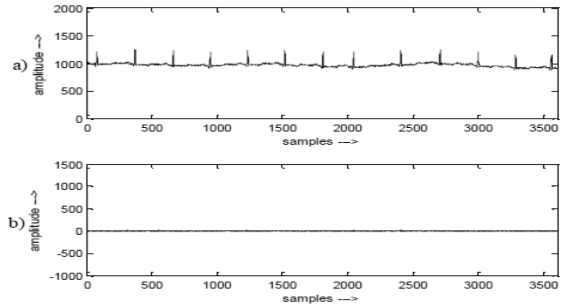

Figure 16: (a) ECG signal after passing through NLMS based filter (b) Error plot after passing through NLMS based adaptive filter

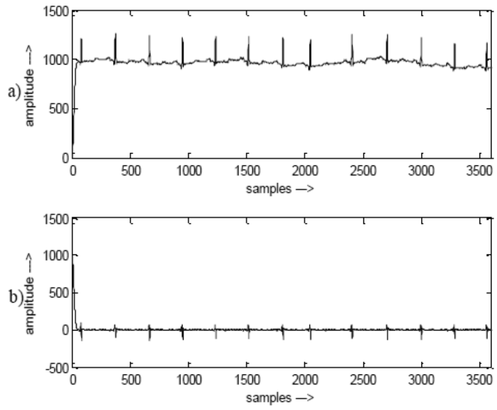

Figure 17: (a) ECG signal after passing through SDLMS based filter (b) Error plot after passing through SDLMS based adaptive filter

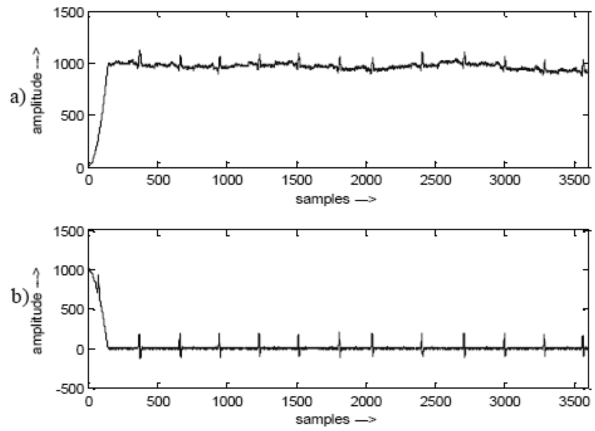

Figure18: a) ECG signal after passing through SELMS based filter (b) Error plot after passing through SELMS based adaptive filter

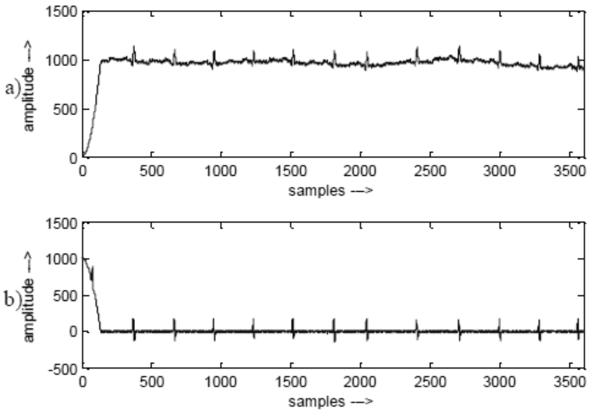

Figure 19: (a) ECG signal after passing through SSLMS based filter (b) Error plot after passing through SSLMS based adaptive filter

All the simulations shown in the above figures are carried out with data no. 100 of MIT-BIH arrhythmia database[3]. To have a comparison of these adaptive filters, the PSNR values are calculated with ECG data 105 and 108 of the database. PSNR values of different adaptive filters are shown in Table 2.

TABLE II
PSNR VALUES OF VARIOUS ADAPTIVE FILTERS

Data No.	LMS	NLMS	SDLMS	SELMS	SSLMS
100	35.58	38.24	37.29	34.63	31.34
105	35.10	37.46	35.22	34.16	32.54
108	32.42	35.36	31.82	31.85	32.53
average	34.37	37.01	34.78	33.54	32.12

The Table 2. Shows the comparative analysis of the PSNR values, The NLMS based adaptive filter gives the better result among all . In case of SDLMS, SELMS and SSLMS based adaptive filters, the computational complexity is decreased at the cost of lower PSNR values. So, NLMS algorithm is preferred when better performance is required. Sign based adaptive algorithms are chosen when faster performance is needed.

E. RESULTS OF WAVELET FILTER BANK BASED DENOISING

For wavelet filter bank based denoising, we have only considered the high frequency noise and the power line interference shown in Figure. 8 and figure 9. These noises are added to the ECG signal shown in Figure.6. After adding the noises, the corrupted ECG signal is shown in figure 20.

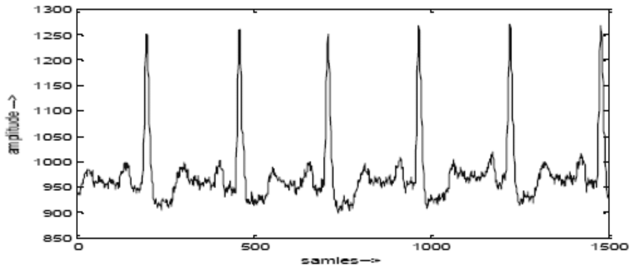

Figure 20:Noisy ECG signal used in wavelet filter bank based denoising

The noisy signal shown in figure 19. is denoised by using discrete wavelet transform. For this, we have chosen *symlet8* wavelet because it has energy spectrum concentrated around the low frequencies like the ECG signal. The *symlet8* wavelet also resembles the QRS complex of the ECG signal. The scaling function φ and wavelet function ψ are shown in figure 21. and figure 22.

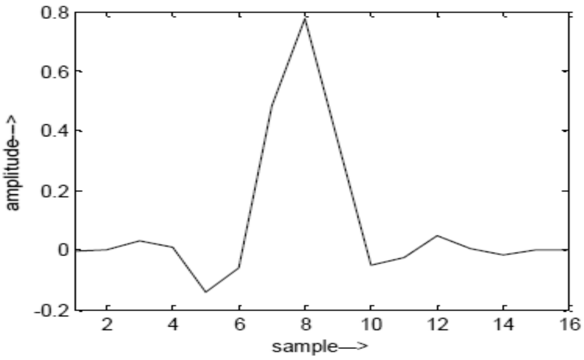

Figure 21:Symlet scaling function φ

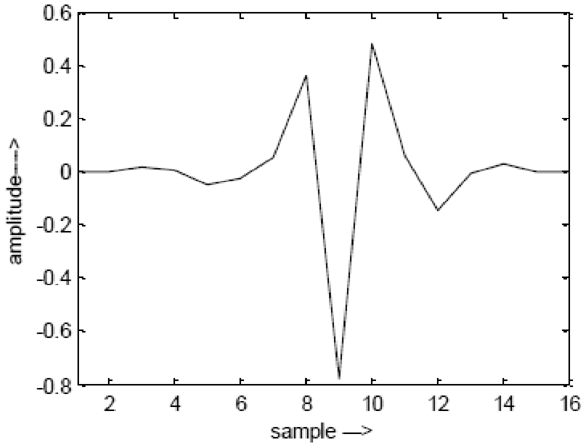

Figure 22:Symlet wavelet function ψ

To remove the power line interference and the high frequency noise, the DWT is computed to level 4 using *symlet8* mother wavelet function and scaling function. The approximate coefficients cAn and cDn at each decomposition level are shown in figure 23. and figure 24. respectively.

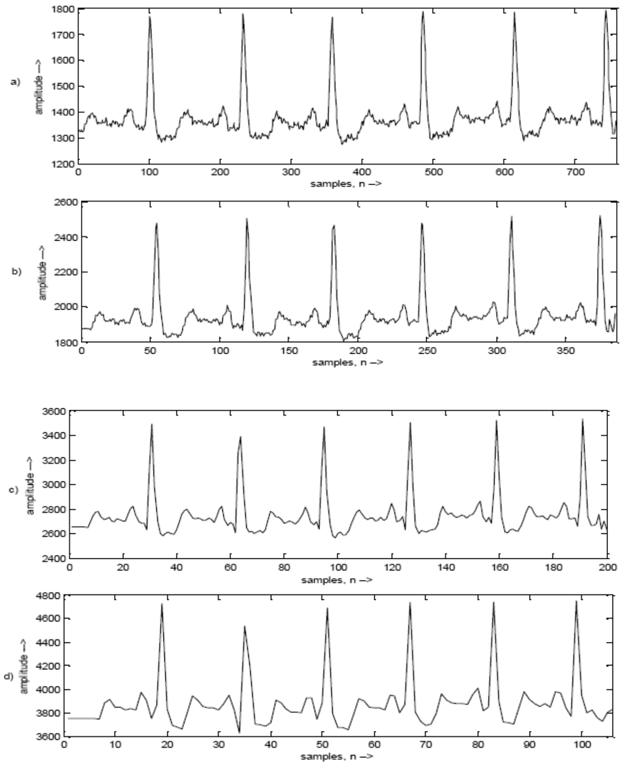

Figure 23:Approximation coefficients at level 1,2,3and 4

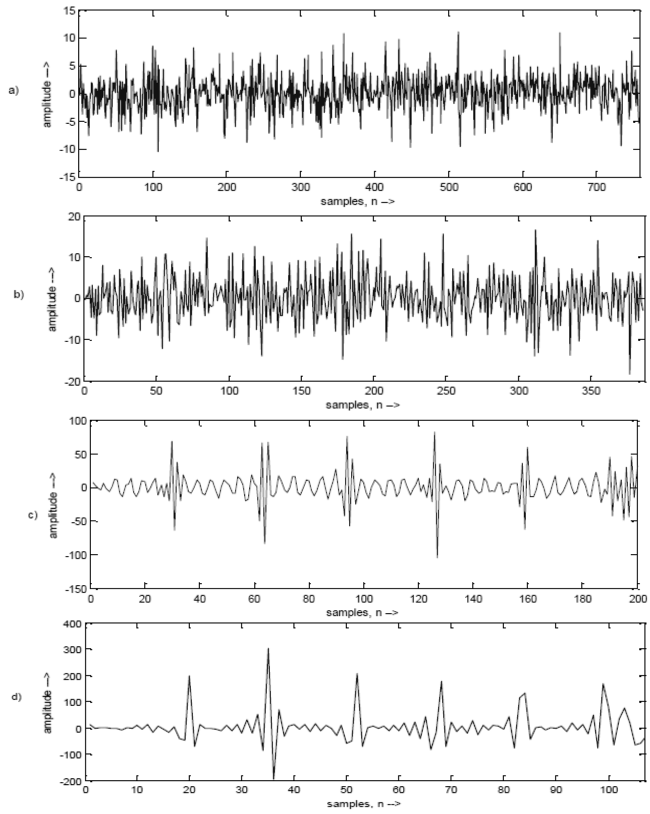

Figure 24:Detailed coefficients at level 1,2,3 and 4.

Then the approximate coefficients at level 4 (cA4) are set to zero. After that, inverse wavelet transform (IDWT) of the modified coefficients are taken to obtain the approximate noise of the ECG signal. The approximated noise signal is shown in figure 25. The residue of the raw signal and the approximate noise is obtained to get noise free ECG signal. The denoised ECG signal is given in figure 26.

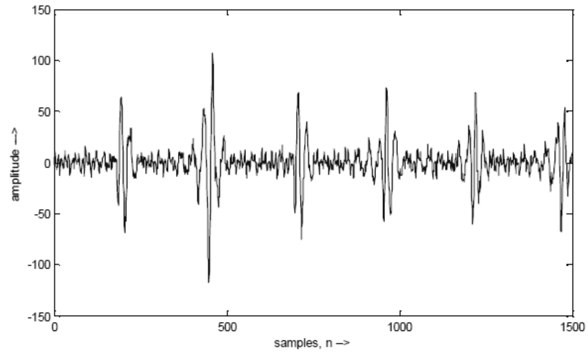

Figure 25: Approximated noise

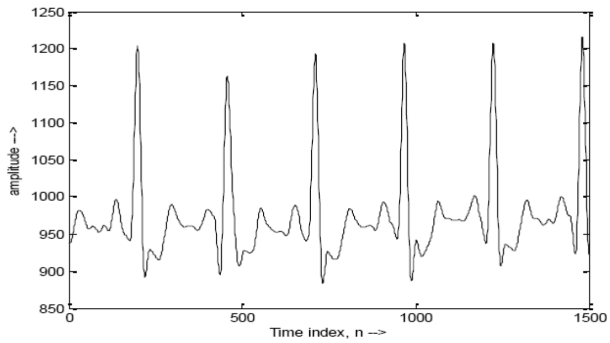

Figure 26:Denoised ECG using wavelet filter bank

CONCLUSIONS

In this thesis we designed and investigated the performance of various Adaptive and Non adaptive filters to remove the artifacts from ECG signal. All the filters are compared with the PSNR values. For the simulations, the ECG signals are taken from the MIT-BIH 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 wavelet filter bank technique.

In first algorithm the Rectangular window based FIR filter gives sharp attenuation and pulsation present in the stop band. The phase response of Rectangular window based filter is linear and the filter is also stable. The second algorithm analyses the performance of different adaptive filters for ECG denoising. In NLMS based adaptive filter, the step size is greater than LMS algorithm and hence the convergence is faster. NLMS based adaptive filter offers better performance than the LMS counterpart. The computational complexity of NLMS is slightly higher. In all the sign LMS algorithms, the computation is faster. So,NLMS algorithm is preferred when better performance is required.

To remove the power line interference and the high frequency noise, the DWT is computed to level 4 using *symlet8* mother wavelet function and scaling function. Then the approximate coefficients at level 4 (cA4) are set to zero. After that, inverse wavelet transform (IDWT) of the modified coefficients are taken to obtain the approximate noise of the ECG signal. The residue of the raw signal and the approximate noise is obtained to get noise free ECG signal. This method removes noise from the ECG signal without any distortion of the ECG signal features.

FUTURE WORK

In this thesis , the window based FIR and LMS algorithm based adaptive filters remove the high frequency, power line interference and low frequency noises. In wavelet filter bank based denoising, only high frequency noise and power line interference are removed. The future developments to this work can be made as follows : 1) Use of other adaptive methods like FT-RLS, QRD-RLS algorithms for ECG denoising. 2) Implementation of wavelet based denoising for the removal of base line wander.

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