International Journal of Engineering Research and General Science Volume 3, Issue 6, November-December, 2015
ISSN 2091-2730

COMPARISON OF ECG SIGNAL DENOISING ALGORITHMS IN FIR AND WAVELET DOMAINS

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Abstract- In the transmission of any signal it is often contaminated with different noises. ECG (electrocardiograph) is the measure of electrical activity of heart and it is used for the diagnosing cardiac diseases, but before the analysis of this ECG signal we have to denoise these signals properly. since ECG is non-stationary signal, wavelet based denoising of ECG signal is considered along with it for simplicity of filters, FIR filters are used and performance of both is compared in terms of signal to noise ratio, time elapsing.

Keywords- ECG, SNR, Window, Thresholding, Wavelet, BLW, PLI, HFN

INTRODUCTION

The ECG signals are analyzed widely for the diagnosis of many cardiac diseases. The electrical signals are traced using non invasive electrodes which are placed on the chest and limbs of the body part. The heart muscle cells which are located in atria and ventricles contract generating electric pulses by self excitable, some cells in the human body are self-excitable, in cardiac system there is also a group of node present which is self-excitable contracting without any signal from the nervous system which are then traced by the ECG. The ECG signals of a normal heart beat consist of three parts: P wave, QRS complex and T wave. The P wave represents the atrial contractions & QRS complex denote ventricle contractions as shown in figure—1 [1. The third wave in an ECG is the T wave. This is produced when the ventricles are repolarising. These waves show sample range of deformities in the ECG signal they are generally contaminated by several types of noises. These include Power Line interference (PLI), Base line wander, muscle contraction and motion artifacts. PLI includes the main part of the distortions at 50-60 Hz. Motion artifacts are the transient baseline changes caused by mismatching of impedance between the electrodes and the skin. [2] Baseline wander is the continuous drifting of the ECG Signal from the baseline. It is mainly caused by respiration and increased body movements [3].

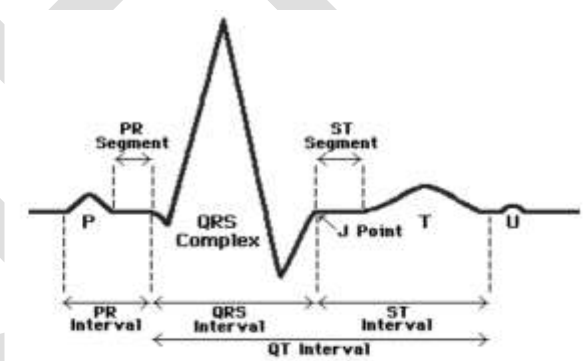

Figure 1 Standard ECG Waveform

Numerous methods have been reported to denoise ECG signals based on filter banks, principal component analysis (PCA), independent component analysis (ICA), neural networks (NNs), adaptive filtering, empirical mode decomposition (EMD), and wavelet transform. The filter bank based denoising process smoothes the P and R amplitude of the ECG signal, and it is more sensitive to different levels of noise [4] Comparatively, the denoising methods based on filter bank and that based on wavelet are compared in reducing noise from the ECG signals. Since, ECG signals are relatively weak and may have strong background noises, the thresholding performed in either FIR or wavelet domain alone will result in an inadequate denoising as far as reliable clinical applications are concerned [5].

DISCRETE WAVELET TRANSFORM

The biomedical signals such as ECG signal, noise reduction is only possible if we using more advanced signal processing method as wavelet denoising technique.

The wavelet transform is similar to the Fourier transform. For the FFT, the basis functions are sine 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.**[6]** The fact that wavelet transform is a multiresolution analysis makes it very suitable for analysis of non-stationary signals such as the ECG signal [7].

$$x(t) = \sum_{k} a_{j0,k} \varphi_{j0,k}(t) + \sum_{j=j0}^{\infty} \sum_{k} b_{j,k}\, \psi_{j,k}(t) \tag{1}$$

Where a, b are the coefficients associated with φj,k(t) and ψj,k(t) respectively.

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules. In other words, this transform decomposes the signal into mutually orthogonal set of wavelets. The scaling function φj,k(n) and the mother wavelet function ψj,k(n) in discrete domain are: The DWT of an discrete signal x(n) . It is quite similar to the Eq. (1)

$$x(n) = \sum_{k} w\, \varphi(j0,k)\varphi_{j0,k}(n) + \sum_{j=j0}^{\infty} \sum_{k} w_{\psi}\,(j_0,k)\psi_{j,k}(n) \tag{2}$$

Here Wφ(j0,k) and Wψ(j0,k) are called the wavelet coefficients. φj,k(n) and ψj,k(n) are orthogonal to each other. Hence we can simply take the inner product to obtain the wavelet coefficients.

FIR FILTER

FIR filters are digital filters with finite impulse response. They are also known as non-recursive digital filters and they do not have the feedback, even though recursive algorithms can be used for FIR filter realization. FIR filters can be designed using different methods, but most of them are based on ideal filter approximation. The objective is not to achieve ideal characteristics, as it is impossible anyway, but to achieve sufficiently good characteristics of a filter. The transfer function of FIR filter approaches the ideal as the filter order increases, thus increasing the complexity and amount of time needed for processing input samples of a signal being filtered.[8]

METHODOLOGY

1. **DENOISING METHODS IN WAVELET DOMAIN**

By applying the wavelet transform, ECG signals were decomposed to the approximate (low frequency component) and detailed (high frequency component) information. Each stage consists of two digital filters and two down samplers by 2.The first filter, g [n] is the high pass filter and h[n] is the low pass filter. The down sampled output of first high pass filter is called detail coefficients (D1) and output of low pass filter is the approximation coefficients (A1).The first approximation (A1) is further decomposed and this process is continued. . The reverse process of combining the coarser approximation and detail coefficients to yield the approximation coefficients at a finer resolution is referred as reconstruction or synthesis [9].

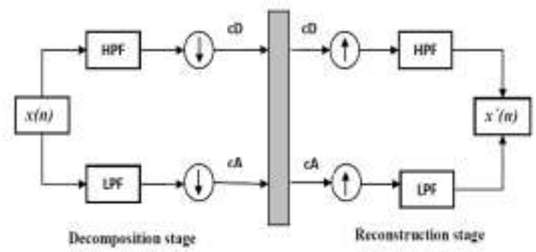

Figure-2 Decomposition and Reconstruction

The general wavelet based method for denoising estimation is to transform the data into wavelet domain, threshold the wavelet coefficients and invert the transform [10].It follows three steps:

1. **Decomposition:** Choose a wavelet, and Compute the wavelet decomposition at level N.
2. **Thresholding**: For each level from 1 to N, select a threshold and apply different thresholding to the detailed coefficients In this step thresholding is used which is major part of wavelet, the selection of right thresholding method will provide better noiseless output .In this paper 4 types of thresholding are used

- 'Rigrsure' uses for the soft threshold estimator.
- 'sqwrlog' uses a fixed-form threshold
- 'Heursure' is a mixture of the two previous options.
- 'Minimaxi' uses a fixed threshold chosen to yield minimax performance for mean square error against an ideal procedure [11] and also applied filters like (haar, db2, db6, db10, bior2.2, bior3.3, coieflet3, coieflet4, symlet4, symlet8).

3. **Reconstruction** after decomposition thresholding is applied to detail coefficients and after that signal is reconstructed by using original approximate coefficients and modified detail coefficients.

2. DENOISING METHODS IN FIR DOMAIN WINDOW METHODS

(1) **Blackman window-** The periodic Blackman window is constructed by extending the desired window length by one sample to N+1, constructing a symmetric window, and removing the last sample. The periodic version is the preferred method when using a Blackman window in spectral analysis because the discrete Fourier transform assumes periodic extension of the input vector. In the symmetric case, the second half of the Blackman window $M \leq n \leq N-1$ is obtained by flipping the first half around the midpoint. The symmetric option is the preferred method when using a Blackman window in FIR filter design The following equation defines the Blackman window of length N.

$$W(n)= 0.42-0.5\cos\left(\frac{2*pie*n}{N-1}\right)+0.08\cos\left(\frac{4*pie*n}{N-1}\right), \quad \text{for } 0<=n<=M-1 \qquad (3)$$

(2) **Hamming window-** an L-point Hamming window using the window sampling specified by 's flag', which can be either 'periodic' or 'symmetric' (the default). The 'periodic' flag is useful for DFT/FFT purposes, such as in spectral analysis. The DFT/FFT contains an implicit periodic extension and the periodic flag enables a signal windowed with a periodic window to have perfect periodic extension. When 'periodic' is specified, hamming computes a length L+1 window and returns the first L points. When using windows for filter design, the 'symmetric' flag should be used. The coefficients of a Hamming window are computed from the following equation.

$$W(n)= 0.54 -0.46\cos\left(2*pie*\frac{n}{N}\right), \quad 0<=n<=N. \qquad (4)$$

The window length is L=N+1

The width of main lobe is approximately 8π /M and the peaks of first lobe are at – 43dB.

(3) **Hanning window-**
The coefficient of a Han window is calculated from the following equation.

ISSN 2091-2730

$$W(n)= 0.54 \ -0.5\cos(2 * pie * \frac{n}{N}), \quad 0<=n<=N. \qquad (5)$$

The width of main lobe is approximately 8π/M and peak of first side lobe is at – 32dB [12].

ANALYSIS METHOD

The first step is to obtain ECG signal form a data base. The data base used for the experiments is MIT-BIH Arrhythmia database, available online [13].All the 48 signals from database has been used for experiment. Wavelet toolbox is used in mat lab. Four different types of thresholding and ten different filters are analyzed for comparison of different techniques and to get the best combination of thresholding and filter. In FIR part all 48 signal is tested against all 3 windows The performance is evaluated in terms of the SNR**,** time elapse **[**14]

$$(1) \qquad \text{SNR (DB)} = \ 10 \ \log_{10}\left(\frac{A^2{}_{signal}}{A^2{}_{noise}}\right) \qquad (6)$$

RESULT AND DICUSSION

(A)**The original ECG signal of 100m**

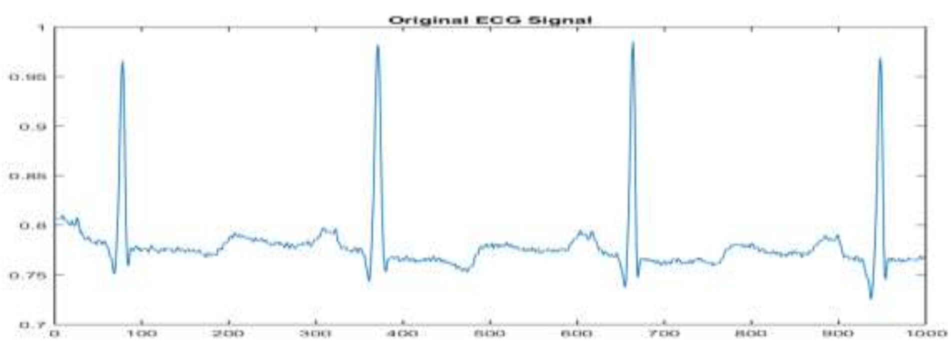

Figure 3 Original 100m.mat signal.

(B)**Generation of Noises**

1. HFN: High frequency noise is generated by multiplying sine wave of 150 Hz frequency with a random signal.

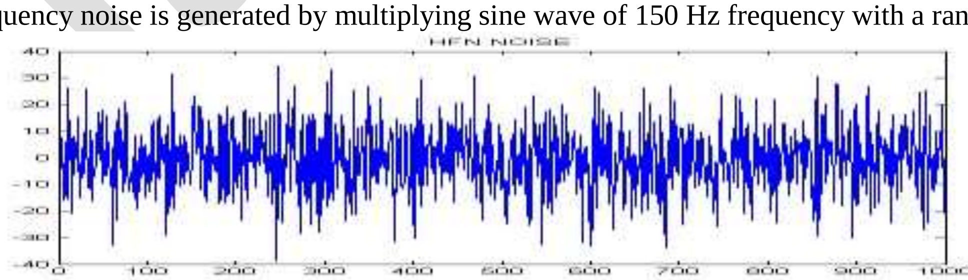

Figure 4 HFN

International Journal of Engineering Research and General Science Volume 3, Issue 6, November-December, 2015
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2. BLW-We generated the baseline drift by adding two sine waves of frequency 0.2 Hz and 0.06 Hz and triangular wave

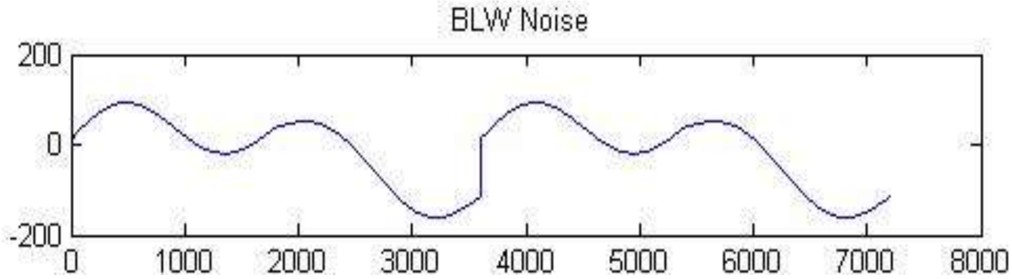

Figure 5 BLW

3. 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.

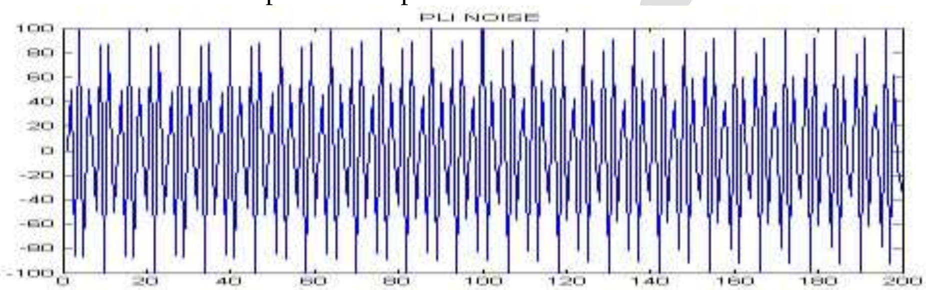

Figure 6 :PLI

(**C) Signal Added with Noises.**

1. HFN added signal

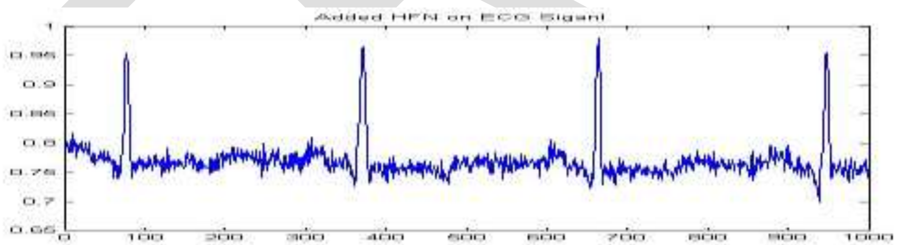

Figure7: noisy ECG signal with HFN

(2)BLW added signal

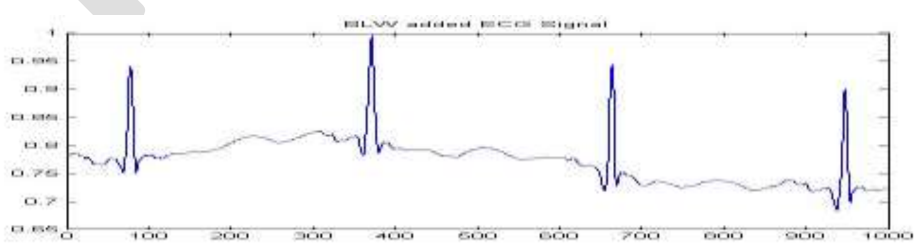

Figure8: Noisy ECG signal with BLW

(3)PLI added signal

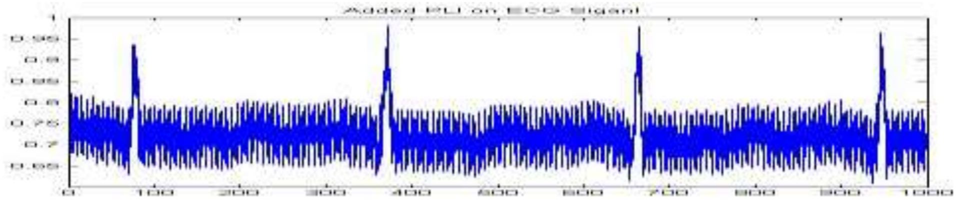

Figure 9 :Noisy ECG is signal with PLI

(D) Wavelet Domain

All the 48 ECG signal from the MIT-BIH database are taken and added with high frequency noise, Power line interference and baseline wonder. The proposed method is applied for all 4 thresholding and different filter (haar, db2, db6, db10, bior2.2, bior3.3, coieflet3, coieflet4, symlet4, symlet8). in wavelet domain. After analyzing 48 signals the noises sym4 and rigrsure thresholding is giving best result so we have shown the result in terms of average of all 48signals SNR. Figure-10, 11, 12 shows the filtered ECG signal.

Table I Average SNR values of 10 filters for high frequency noise

SIGNAL	AVG OF 48
HAAR	**38.13648**
DB2	**39.09739**
DB6	**39.42064**
DB10	**39.40012**
SYMLET4	**39.3974**
SYMLET20	***39.45396***
BIOR2.2	**38.13648**
BIOR3.3	**39.18837**
COIEF3	**39.12079**
COIEF4	**39.41658**

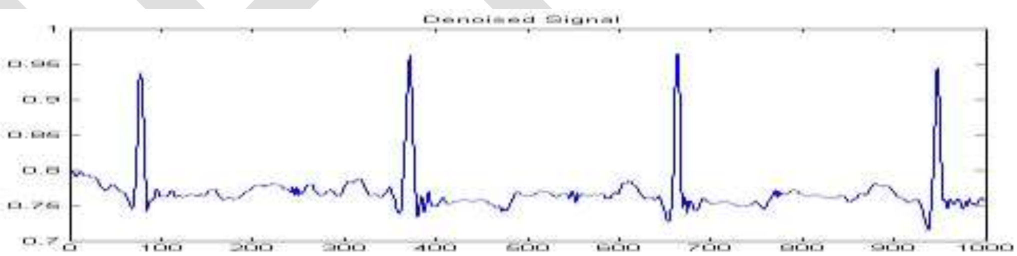

Figure 10: Filtered ECG signal for HFN for sym20.

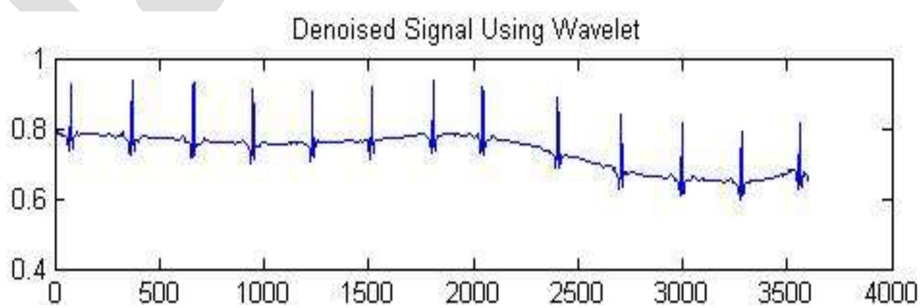

Figure 11: Filtered ECG signal for BLW for sym4.

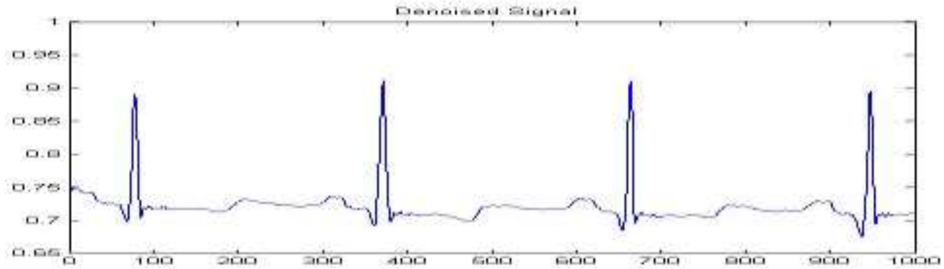

Figure 12 : Filtered ECG signal for PLI for sym20.

(E) FIR domain:
All 48 signals are applied to 3 window techniques Blackman, hamming and hanning. Among which Blackman window is giving best result.

Table II Average SNR values of 3 window for high frequency noise

Window	**SNR**
HAMMING	**37.04833**
HANNING	**37.05351**
BLACKMAN	***37.07339***

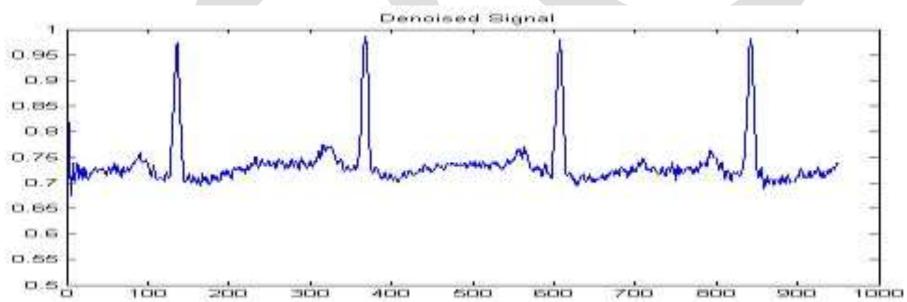

Figure 13:filtered ECG signal in HFN for Blackman window.

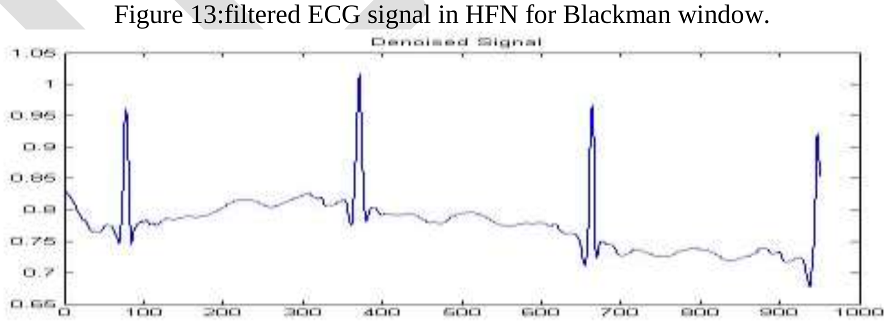

Figure 14: filtered ECG signal in BLW for Blackman window.

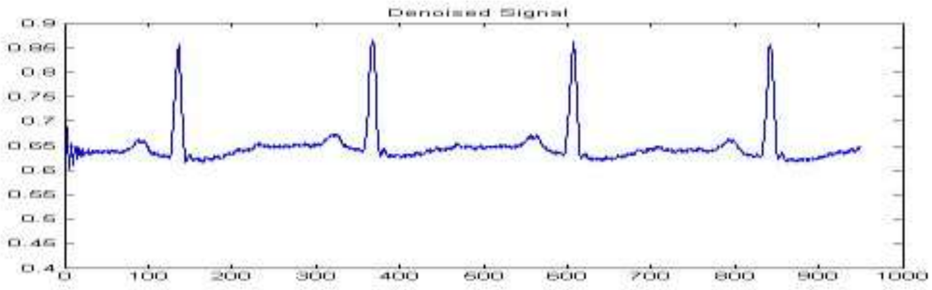

Figure 15: filtered ECG signal in PLI for hanning window.

COMPARISON OF WAVELET AND FIR

From the above table we can easily compare the performance of wavelet and FIR filter on the basis of SNR, TIME ELAPSING. Here we took the best methods of both the filtering.

(1) SIGNAL TO NOISE RATIO

Table III comparison of sym4 and Blackman on the basis of SNR

NOISES	AVG OF 48 SIGNALS (WAVELET)	AVG OF 48 SIGNALS BLACKMAN(FIR)
HFN	*39.45396*	33.55802
PLI	*18.26185*	17.00761
BLW	*21.7968*	20.05052

(2)TIME ELAPSING

Table IV comparison of sym4 and Blackman on the basis of time elapsing

NOISES	AVG OF 48 SIGNALS SYM4(WAVELET)	AVG OF 48 SIGNALS BLACKMAN(FIR)
HFN	*0.421366*	0.001746
PLI	*0.399985*	0.001755
BLW	*0.12686*	0.001709

CONCLUSION-

ECG signals are affected by different noise sources like high frequency noise, power interference and baseline wandering. In this paper we propose a denoising technique based on discrete wavelet transform and FIR filter and answer is compared in terms of SNR. From the filtered figure it can be easily concluded that wavelet filter is giving better ECG graph. In the table-III SNR is compared of Wavelet and FIR, wavelet is again giving better result for all of the three noises. In the table IV time requirement for execution of process is compared here result is opposite of previous. For FIR time elapsing is less.

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