Finite Impulse Response Bank Filter for Electroencephalographic Artifacts Removal

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Abstract

The recording of brain's electrical activity over a period of time is called electroencephalogram EEG signal. EEG became cardinal tool for diagnosing and managing malfunctions and various brain disorders. It is very complex to analyze continuous EEG signals. These signals can be categorized to different kinds according to the frequency: Delta (0.5 – 4Hz), Theta (4 −7.5Hz), Alpha (7.5 – 12Hz), Beta (12 −30Hz), and Gamma (above 30Hz). Since EEG signals are categorized by their very small amplitudes, they can be easily polluted by noise. These noises are called the artifacts. These artifacts need to be removed before processing and analyzing the EEG signal. In general, an EEG signal which represents brain neuronal activity is contaminated with noises, artifacts, and external interferences. Therefore it is important to separate the required frequency band information from such noises. Different methods for noise and artifact removing are available and implemented. Filtering these interference signals might remove some relevant EEG information, and therefore care must be taken while choosing one of the preprocessing methods. This paper presents a detail analysis of EEG de-noising using law pass Butterworth filter, packet wavelet transforms (PWT), and FIR bank filter. All the above methods are simulated and tested using MATLAB 2013 software environment and their performance evaluation can be done by measuring the parameters like SNR, PSNR, MSE and MAE. The EEG database is freely acquired from MIT-BIH arrhythmia database. This EEG signals was polluted with white random external noise. The FIR bank filter gives the optimal noise removal results according to measuring parameters.

Keywords: EEG, Butterworth filter, PWT, FIR bank filter, SNR, PSNR, MSE, MAE.

استخدام المرشح البنكي الرقمي ذو الاستجابة المحدودة لازالة الضوضاء من اشارة التخطيط الدماغي

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المستخلص

عملية تسجيل النشاط الكهربائي للمخ على مدى فترة من الزمن تسمى إشارة التخطيط الدماغي الكهربائي EEG. التخطيط الدماغي أصبح أداة أساسية لتشخيص امراض واضطرابات الدماغ المختلفة. عملية تحليل إشارات EEG تعتبر من العمليات المعقدة. ويمكن تصنيف اشارة EEG إلى أنواع مختلفة من الاشارات وفقا للتردد: دلتا (0.5 – 4 هرتز)، ثيتا (4- 7.5هرتز)، ألفا (7.5-12 هرتز)، بيتا (12-30 هرتز)، وغاما (فوق 30 هرتز). بما ان إشارات EEG تتميز بالسعة القليلة جداً، لذا يمكن أن تلوث بسهولة بالضوضاء. قبل معالجة وتحليل اشارات EEG يجب ازالة هذه الضوضاء. وبصفة عامة، إشارة EEG التي تمثل نشاط الخلايا العصبية في الدماغ تكون ملوثة

بالضـــوضـــاء، والتداخلات الخارجية. ولذلك من المهم عزل المعلومات الموجودة في حزم التردد عن هذه الضـوضـاء. تم تنفيذ وتصـميم أسـاليب مختلفة لازالة الضـوضـاء. بعض المعلومات المتوفرة في اشارة EEG قد تفقد عند ازالة الضوضاء لذا يجب توخي الحذر في اختيار الطريقة المناسبة. في هذا البحث نعرض تحليل تفصيلي لازالة الضوضاء من اشارة التخطيط الدماغي باسـتخدام مرشـح بتروورث للترددات القليلة ، مرشـح تحويلات حزمة المويجات (PWT)، والمرشـح البنكي الرقمي المعروف بالمرشـح ذو الاسـتجابة المحددة(FIR) . تم تنفيذ ومحاكاة جميع المرشـــحات المذكورة باســـتخدام بيئة ماتلاب 2013 . تقييم اداء المرشـحات تمت عن طريق قياس مجموعة من البارالميترات مثل نسـبة الاشـارة الى الضـوضـاء (SNR)، اعلى نسبة اشارة الى الضوضاء (PSNR) ، الوسط التربيعي للخطا (MSE) ، و الوسـط المطلق للخطا (MAE). تم تجميع بيانات التخطيط الدماغي من الانترنيت عبر موقع MIT– BIH الخاص ببيانات ضربات القلب وتخطيط الدماغ. قبل تمرير اشـارة EEG على المرشـحات تم اضـافة ضـوضـاء خارجية عشـوائية لتلويث الاشـارة الاصـلية. المرشـح البنكي الرقمي اعطى افضـل الطرق ازالة الضـوضـاء وفقا للبارامترات المقاسة.

الكلمات المفتاحية: التخطيط الدماغي الكهربائي، الخلايا العصـــبية، امراض اضـــطرابات الدماغ

INTRODUCTION

The electrical activity of the brain is measured using different electrodes on the scalp. This type of measurement is a noninvasive. The recording of brain's electrical activity over a period of time is called electroencephalogram (EEG) signal. EEG became cardinal tool for diagnosing and managing malfunctions and various brain disorders [1]. It is also used to determine brain death.

It is very complex to analyze continuous EEG signals. These signals can be categorized to different kinds according to the

frequency: Delta (0.5 – 4Hz), Theta (4 –7.5Hz), Alpha (7.5 – 12Hz), Beta (12 –30Hz), and Gamma (above 30Hz). Since EEG signals are categorized by their very small amplitudes, they can be easily polluted by noise [2]. This noise can be categorized to two types: external noise (electrode noise) and internal noise (noise generated from the human during the tests like eye movements). These noises are called the artifacts. For the suitable analysis of EEG signals, these artifacts need to be eliminated from the raw signals [3].

In general, an EEG signal which represents brain neuronal activity is contaminated with noises, artifacts, and external interferences. Therefore it is important to separate the required frequency band information from such noises. Different methods for noise and artifact removing are available in the literature. Filtering these interference signals might remove some relevant EEG information, and therefore care must be taken while choosing one of the preprocessing methods. Adaptive filtering is applied by He *et al.* [4] to remove ocular artifacts. Adaptive filtering and independent component analysis (ICA) is deployed to minimize movement of the eyes has been applied by Romero *et al.* [5]. Novel adaptive method performed by empirical mode decomposition (EMD) has been applied by Zeng *et al.* [6]. Principal component analysis (PCA) incorporates a Math procedure, which derives several (probably) correlated variables and a number of uncorrelated variables termed as principal components has been applied by Dong Kang; LuoZhizeng as a method to de-noise the EEG signal [7]. Kalman Filter (KF) has been employed by Shahabi for detection, and artifacts removal with good results [8]. Priyanka Khatwani [9] did a study to eliminate ocular artifacts deploying ICA, PCA and wavelet transform; deriving at a conclusion that wavelet method gave the most de-noising result due to its multi-resolution capacities. Wavelet transform analyses the signals in frequency and time domain and also signals that have low noise amplitudes could be eliminated from signals by choosing the best wavelet to decompose the signal.

In the present paper Butterworth filter, packet wavelet transforms (PWT), and FIR bank filter are implemented to remove artifacts from EEG signal. All the above methods are simulated using MATLAB 2013 software environment and their performance evaluation can be done by measuring the parameters like SNR, PSNR, MAE and MSE etc.

METHODOLOGY

The EEG database in our paper is acquired from internet websites, PHYSIONET MIT-BIH arrhythmia database [10]. This EEG signals were sampled at a sampling frequency of 256Hz. The white Gaussian noise that we are applied contaminates the recorded signals. In this paper we implemented three methods to suppress this noise. The packet wavelet transform, Butterworth filter, and FIR bank filter are the three methods studied. The original signal is assumed as $o(n)$ and the noise is assumed as $e(n)$.

$$s(n) = o(n) + e(n) \tag{1}$$

(A) Packet wavelet transforms (PWT)

Wavelets are functions that induce designated demand. The main wavelet characteristics is it has zero integration, oscillating below and above the x– axis. Wavelets are used as essential functions to substitute other waves. In signal processing, non–stationary signals can be represented by wavelets with less coefficients than by Fourier functions since wavelets are located in time and frequency while the Fourier are localized in frequency only [11].

The Wavelet Transform purveys a time–frequency spectrum of the signal. By wavelet transform, the signal is expressed as a linear combination of the sun of the product of the mother wavelet and the wavelet coefficients. The wavelet transform is given by [12]:

$$X_w\,(c,d) = \frac{1}{\sqrt{c}} \int_{-\infty}^{\infty} K * \left\{\frac{t-d}{c}\right\} X(t)dt \qquad (2)$$

Where X(t) is the original signal, c & d are wavelet function parameters. In wavelet de–noising techniques the signals are decomposed into high frequency components and low frequency components using thresholding method. Hard thresholding & soft thresholding are the two methods available for thresholding. Before reconstructing the original signal and for best decomposing the noisy signal it needs to select the suitable wavelet from the wavelet families [13]. Packet wavelet transform can be illustrated as filtering the noisy signal by a bank of filters of non–overlapping bandwidths which vary by an octave. It is based on sub–band coding which is found to yield a fast calculation of Wavelet Transform. PWT is carried out by repeated filtering of the input signal using two filters. Low pass filter (LPF) and high pass filter (HPF) are used to decompose the noisy signal into different scales. The approximation coefficient is the output gained by LPF. It is in the form of [12]:

$$\varphi(t) = 2\ \sum_{q=0}^{M} h\ (q)\ \varphi\ (2t - q) \qquad (3)$$

The detailed coefficient is the output gained by HPF. It is in the form of:

$$w(t) = 2\ \sum_{q=0}^{M} g\ (q)\ \varphi\ (2t - q) \qquad (4)$$

The bank filters bandwidth is inversely proportional to the level of decomposition. The total sub bands are (2^{l}), and the bandwidth of each sub band at level "l can be evaluated as:

$$\left\{\frac{n\,f_s}{2^{l+1}}\ ,\frac{(n+1)f_s}{2^{l+1}}\right\} \qquad \text{n=0,1,2, -----------, } 2^{l-1}\ ;\ f_s$$

is the sampling frequency.

In this paper, the sampling frequency used was 256 Hz and the noisy signal was subjected to 5 level of decomposition. Then Δf of each sub band can be calculated as 4Hz according to:

$$\Delta f = \frac{f_s}{2^{l+1}} \qquad (5)$$

Figure (1) illustrates the packet wavelet transform tree.

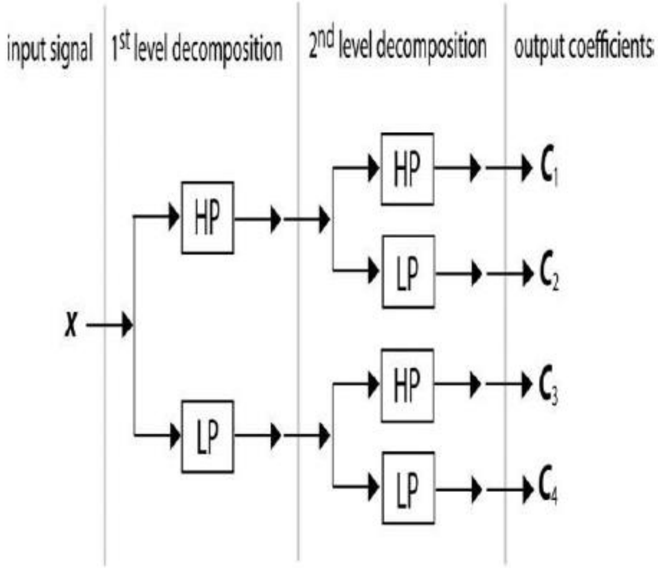


Fig. (1) PWT decompose tree

(B) Butterworth filter

The most commonly digital filters used in signal analysis are Butterworth filters since they are high speed and simple implementation. The Butterworth filter is a signal processing filter. The main features of this filter can be summarized as it has a flat frequency response as possible (no ripples) in the pass-band and zero roll off response in the stop-band. It is frequency based so that the effect of filtering can be comprehended and expected easily. However, the main disadvantage of Butterworth filter is that it has poor phase characteristics. Figure (2) illustrate the low pass Butterworth filter frequency response. We can conclude from the figure that as the order (n) of the filter increased (i.e. higher number of cascaded stage in filter design), the filter response approximate to ideal low pass filter [14].

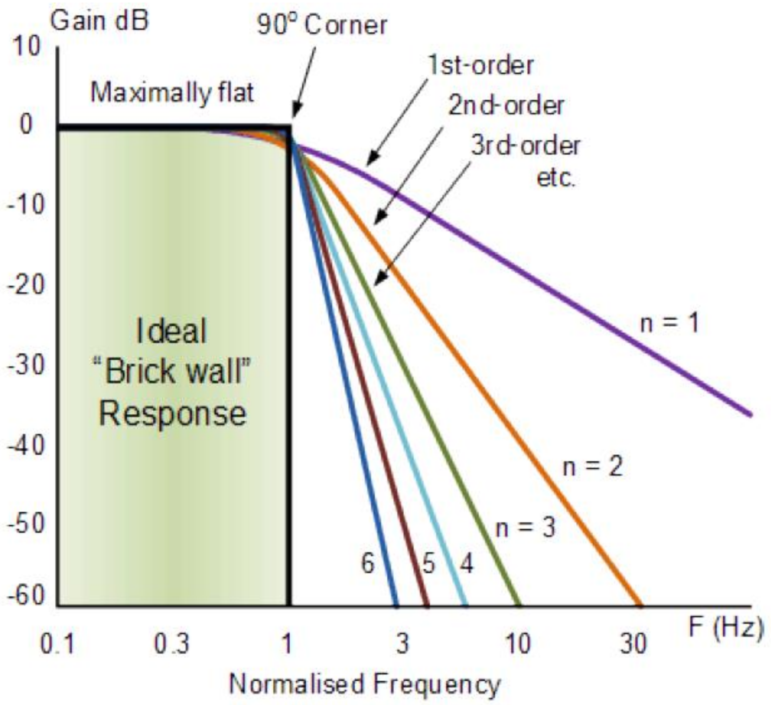


Fig. (2) Butterworth low pass filter response

The squared magnitude function of n^{th} order low pass Butterworth filter can be approximately described as [15]:

$$|H(j\omega)|^2 \approx \frac{1}{1+(\frac{\omega}{\omega c})^{2n}} \qquad n=1,2,\ldots\ldots \quad (6)$$

Where ωc represent 3 dB cutoff frequencies.

Properties of this equation are:

- ❖ $|H(j0)|^2 = 1$
- ❖ $|H(j\infty)|^2 = 0$ (i.e. the Butterworth filter response is approximately flat at $\omega = 0$)
- ❖ $|H(j\omega c)|^2 = \frac{1}{2}$ for all n
- ❖ Poles never occur on the imaginary s –plane curve. They occur on the real axis only for odd values of n.
- ❖ The poles are spaced equidistant on the unit circle, which means equal angles between poles.

- Stability is obtained by selecting the poles lying in the left half plan.

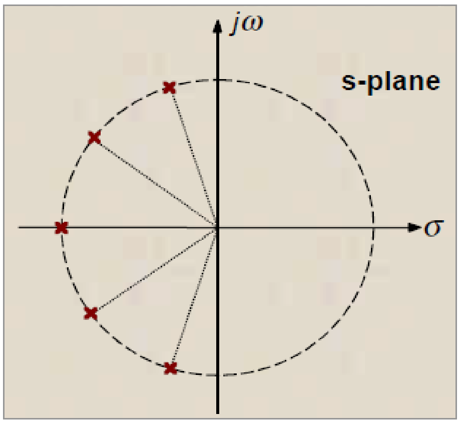


Fig. (4) 5^{th} order Butterworth filter s – plane

<u>(C) FIR bank filter</u>

The necessary component digital signal processing algorithms are filter–banks, which have many applications such as in sub band coding, multi rate communication systems, frequency multiplexing, audio graphic equalizers, & noise reduction systems. The filter bank traditional form is a parallel formation of band pass filters as illustrated in figure (5). According to the energy contents of the different bands, the sub band filters may be uniformly spaced in the frequency domain or they may be spaced non–uniformly. Sub bands with equal bandwidth represent uniformly spaced type. The band pass filters that construct a bank filter can be FIR filters or IIR filters [16].

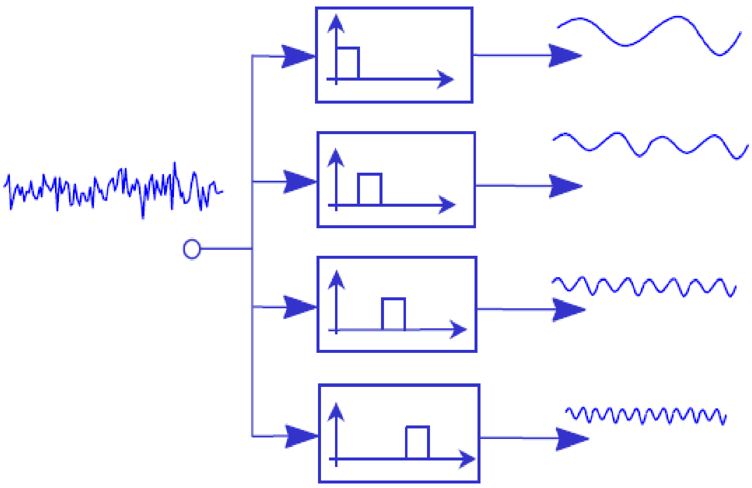


Fig. (5) Four bands filter bank configuration block diagram

In our paper, we design linear phase uniformly spaced FIR filter banks using windows. The sub band bandwidth is 4Hz. The design procedure can be summarized by the following steps [16]:

- First, we design a low pass filter with a bandwidth of 4Hz. The impulse response of this filter is obtained via inverse Fourier transform as:

$$h_d(m) = \int_{-fc}^{fc} 1\, e^{j2\pi mf}\, df \qquad (7)$$

- To obtain an FIR filter of order M we multiply $hd(m)$ by a rectangular window sequence of length $M+1$ samples centered at $m=0$. To introduce causality ($h(m)=0$ for $m < 0$) shift $h(m)$ by $M/2$ samples.
- To design the band pass filters we used the amplitude modulation technique to translate a low pass to band pass filter.

- To translate this low pass filter to the specified band pass filters we need AM sinusoidal carriers for each sub band.

1. SIMULATION AND RESULTS

The EEG signal is collected from the MIT databases which enclose the signals without noise. The white noise with different variances (0.2 to 2 with 0.2 steps) is added to the signal by using a MATLAB program. Then this signal is applied to three filters packet wavelet, low pass Butterworth, & FIR bank filter. Variety of statistical parameters are then calculated (SNR, PSNR, MSE, &MAE) to distinguish between the performance of the three filters.

SNR (Signal to Noise Ratio)

It is a measure of how strong the signal is compared to the noise. The ratio between the signal power and the noise power is the signal to noise ratio.

$$SNR = \frac{Psignal}{Pnoise} \qquad (8)$$

SNR is usually represented in decibels (dB):

$$SNR = 10 \log \left(\frac{Psignal}{Pnoise}\right) \qquad (9)$$

PSNR(Peak Signal to Noise Ratio)

It is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It is usually expressed in terms of the logarithmic decibel scale. PSNR is most easily defined via the mean squared error (MSE):

$$PSNR = 10 \log \left(\frac{MAX^2}{MSE}\right) = 20 \log \left(\frac{MAX}{\sqrt{MSE}}\right) \qquad (10)$$

MSE(Mean Square Error)

It is the average of the squared error between original and de-noised signal. Squaring the difference removes the possibility of dealing with negative numbers. MSE is widely used in signal processing applications.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{i=N}(Si - Yi) \qquad (11)$$

Where, S_i represents the original signal, Y_i represents the de-noised signal and N represents the length of the signal.

MAE(Mean Amplitude Error)

It is a quantity used to measure how close de-noised signal is to the original signal. It is common used in time series analysis. As the name suggests, the mean absolute error is an average of the absolute error $|ei| = |(Yi - Si)|$.

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{i=N}|Yi - Si| = \frac{1}{N} \sum_{i=1}^{i=N}|ei| \quad (12)$$

Results:

The proposed system and the measuring parameters were implemented and simulated using MATLAB 2013 software environment. For testing the algorithms, EEG signal was collected from PHYSIONET MIT-BIH arrhythmia database. It was sampled at 256Hz sampling frequency. This signal was contaminated with Gaussian noise of different variance from 0.2 to 2 on step of 0.2. Figure 6 shows the original EEG signal, artifacts at variance of 2, and EEG signal contaminated with noise.

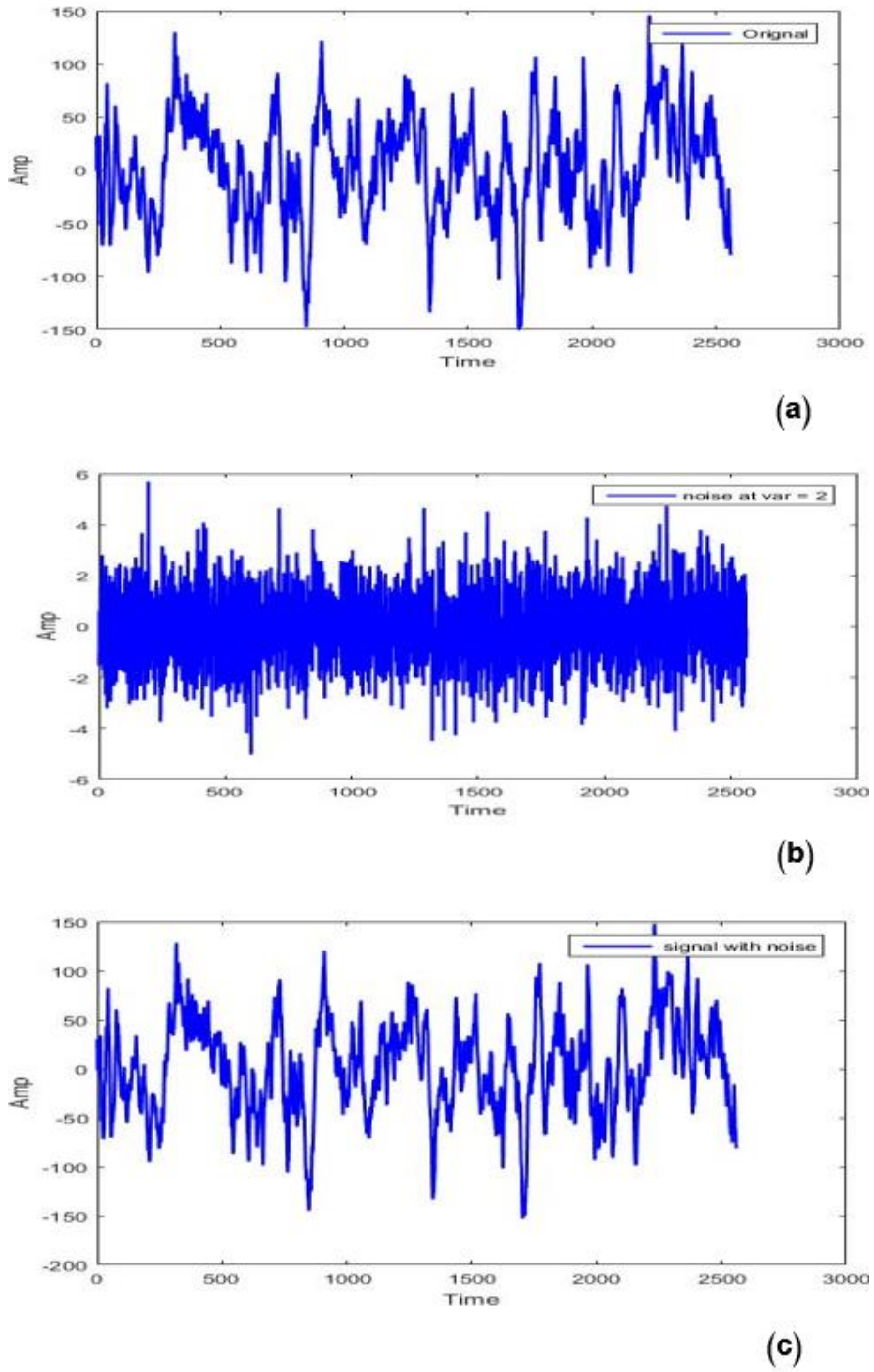
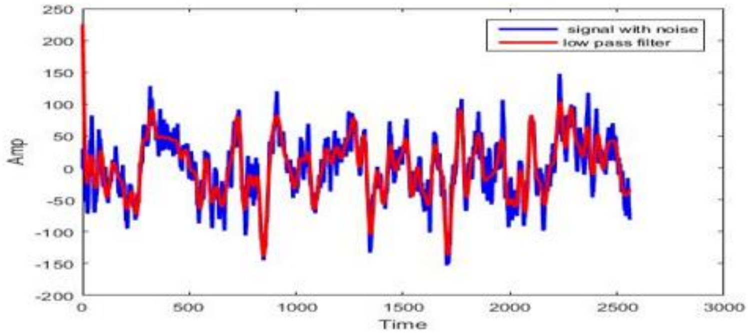
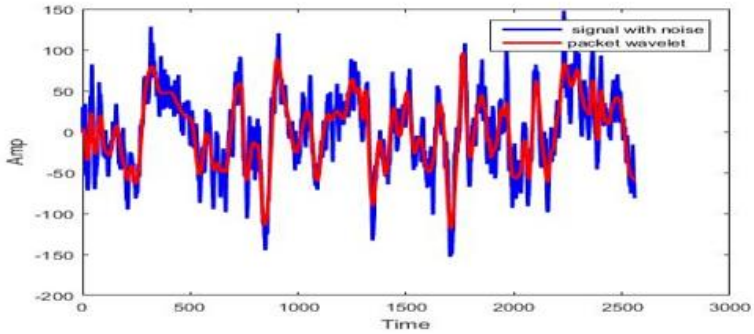


Fig. (6) EEG signal (a) Original EEG signal. (b) Noise at variance 2. (c) Original signal contaminated with noise

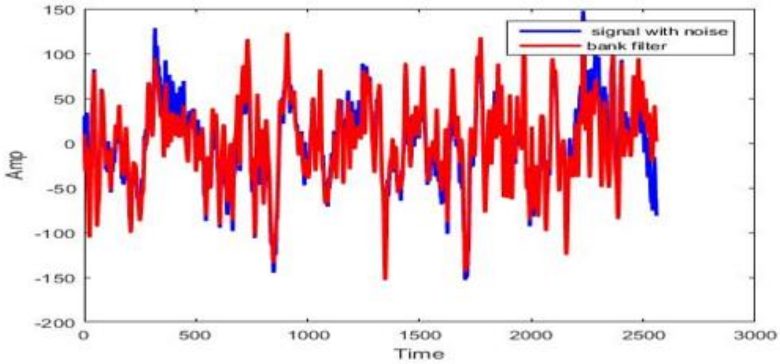
This signal was then applied to three type of filters (low pass Butterworth filter, packet wavelet transforms (PWT), and FIR bank filter). Figure 7 illustrates comparison of the original signal with noise and the resulted de-noised signal of the three filter techniques used (with noise variance of 2).



(a)



(b)



(c)

Fig. (7) De-noised signals using (a) Low pass Butterworth filter. (b) Packet wavelet filter. (c) FIR bank filter.

Finally the measured parameters (SNR, PSNR, MSE, MAE) for ten different noise variances (from 0.2 to 2 in step of 0.2) were tabulated in table 1 through 4 respectively.

Table (1) SNR measurement for different noise variance

	signal to noise ratio SNR									
	Noise Variance									
Type of Filters	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2
Butterworth filter	17.354	17.354	17.366	17.352	17.356	17.361	17.336	17.366	17.343	17.383
FIR bank filter	18.107	18.086	18.103	18.092	18.119	18.102	18.052	18.051	18.091	18.097
PWT filter	17.453	17.455	17.451	17.455	17.455	17.454	17.443	17.458	17.457	17.46

Table (2) PSNR measurement for different noise variance

	Peak Signal to Noise Ratio PSNR									
	Noise Variance									
Type of Filters	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2
Butterworth filter	26.972	26.972	26.985	26.971	26.974	26.979	26.955	26.985	26.961	27.002
FIR bank filter	27.725	27.704	27.722	27.71	27.738	27.72	27.671	27.67	27.709	27.716
PWT filter	27.071	27.074	27.069	27.073	27.073	27.072	27.061	27.077	27.075	27.078

Table (3) MSE measurement for different noise variance

	Mean Sequare Error MSE									
	Noise Variance									
Type of Filters	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2
Butterworth filter	4.051	4.046	4.828	4.186	4.851	4.355	4.746	4.794	4.129	4.152
FIR bank filter	3.921	3.643	3.176	3.147	3.878	3.308	3.457	3.517	3.239	3.687
PWT filter	4.384	4.171	4.56	4.206	4.215	4.301	4.374	4.853	4.981	4.708

Table (4) MAE measurement for different noise variance

	Mean Amplitude Error MAE									
	Noise Variance									
Type of Filters	0.2	0.4	0.6	0.8	1	1.2	1.4	1.6	1.8	2
Butterworth filter	5.278	5.278	5.274	5.269	5.274	5.273	5.28	5.282	5.285	5.265
FIR bank filter	4.605	4.639	4.627	4.643	4.595	4.618	4.655	4.644	4.65	4.597
PWT filter	6.511	6.505	6.513	6.506	6.504	6.504	6.534	6.496	6.497	6.505

It is clear from the above results that the FIR bank filter gives the optimal solution for EEG noise removal according to SNR, PSNR, MSE, & MAE parameter measurements.

CONCLUSION

EEG analysis requires accurate information. Usually, these signals are polluted to various noises. Before EEG processing these noises must be removed.

In this work, low pass Butterworth filter, packet wavelet filter, & FIR bank filter was successfully simulated and tested in removing noises from EEG signal. Figure 7 demonstrated that the bank filter has a slight advantage on minimum signal distortion as compared with the other two methods. Also according to the measuring parameters SNR, PSNR, MSE, & MAE the FIR bank filter has a venial privilege on the results over the other two methods as illustrated on tables 1 through 4. These parameters were measured according to ten noise variances values (0.2 to 2). It is concluded that the FIR bank filter gives less complexity and easier to removal of the EEG artifacts over the packet wavelet transform which needs to accurate on selection the mother wavelet and the threshold.

References

[1] Yongjian Chen , *Neural Network Based EEG Denoising*, 30th Annual International IEEE EMBS Conference Vancouver, British Columbia, Canada, August 20-24, 2008.

[2] Mrs V Baby Deepa ,Dr P Thangaraj, Dr S Chitra, *Investigating the performance improvement by sampling techniques in EEG data*,

International Journal on Computer Science and Engineering , Vol.2,Jun.2010,pp:2025-202.

[3] Anderer Pet, "Artifact processing in computerized analysis of sleep EEG," *Neuropsychobiology*, Sep 1999, Vol.43, No.3, pp.150-157.

[4] He, P.; Wilson, G.; Russell, C. Removal of ocular artifacts from electro-encephalogram by adaptive filtering. *Med. Biol. Eng. Comput.* 2004, *42*, 407–412.

[5] Romero, S.; Mananas, M.; Barbanoj, M.J. Ocular reduction in EEG signals based on adaptive filtering, regression and blind source separation. *Ann. Biomed. Eng.* 2009, *37*, 176–191.

[6] Zeng, H.; Song, A.; Yan, R.; Qin, H. EOG artifact correction from EEG recording using stationary subspace analysis and empirical mode decomposition. *Sensors* 2013, *13*, 14839–14859.

[7]Dong Kang; LuoZhizeng; ,*A Method of Denoising Multi-channel EEG Signals Fast Based on PCA and DEBSS Algorithm*, Computer Science and Electronics Engineering (ICCSEE), 2012 International Conference on ,vol.3, no., pp.322-326, 23-25 March 2012.

[8] Shahabi, Hossein, Moghim, Sahar, Zamiri-Jafarian, "EEG eye blink artifact removal by EOG modeling and Kalman filter," *Biomedical Engineering and Informatics (BMEI),* 2012, Oct. 2012, pp.496-500.

[9] Priyanka Khatwani, Archana Tiwari, "*A survey on different noise removal techniques of EEG signals*",International Journal of Advanced Research in Computer and Communication Engineering, Vol. 2, Issue 2, February 2013

[10] https://www.physionet.org/cgi-bin/atm/ATM.

[11] Krishnaveni, V.; Jayaraman, S.; Aravind, S.; Hariharasudhan, V.; Ramadoss, K. "*Automatic identification and removal of ocular artifacts from EEG using wavelet transform*". *Meas. Sci. Rev.* 2006, *6*, 45–57.

[12]Geeta Kaushik, H.P.Sinha, Lillie Dewan, " *Biomedical Signals Analysis by Dwt Signal Denoising with Neural Networks*", International Journal of Recent Trends in Electrical & Electronics Engg., Dec. 2013. ©IJRTE ISSN: 2231-6612

[13] Priyanka Khatwani, Archana Tiwari, "*A survey on different noise removal techniques of EEG signals*", International Journal of Advanced Research in Computer and Communication Engineering Vol. 2, Issue 2, February 2013.

[14] Selesnick, I.W., and C.S. Burrus.,"*Generalized Digital Butterworth Filter Design*", Proceedings of the IEEE Int. Conf. Acoust., Speech, Signal Processing, Vol. 3, May 1996.

[15] Les Thede, "*Practical Analog and Digital Filter Design*",Artech House, Inc., 2004.

[16] T. Saramaki and R. Bregović. "Multirate Systems and Filter Banks",G. Jonanovic-Dolecek, editor, *Multirate Systems: Design & Application*, chapter 2, pp. 27–85. Idea Group Publishing, Hershey, Pennsylvania, 2002

[17] Sophocles J. Orfanidis,"*introduction to signal processing*", FIR digital filter design, chapter 10, Prentice Hall, Inc. Previous ISBN 0-13-209172-0,2010.