Comparative Analysis of Various Filtering Techniques for Denoising EEG Signals

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Abstract- **Electroencephalography (EEG) provides diagnostic information related to various brain disorders. Various types of interferences, like line interference, EOG, and ECG, muscle movement, cause artifacts in EEG data. Therefore, denoising EEG data plays a vital role in preserving the specific frequency content of the signal. Several filtering techniques are available to detach the noise to preserve the integrity of EEG signals. In this paper, we have compared different filtering techniques i.e., Adaptive filters, LPF Butterworth filter, Notch filter, wavelets on epileptic EEG signals, and sleep EEG signal. Our result suggests that the wavelet transform is the best option for denoising the EEG signal as it is more efficient in denoising the EEG signal without losing the original information. To select the best suitable wavelet function for denoising, Symlet4, Haar, Daubechies4, Biorthogonal2.6, Coiflets3, Discrete Meyer, Reverse Biorthogonal 6.8, Reverse Biorthogonal 2.8 has been used, and it is observed that wavelet function Bio-orthogonal 2.6 is the best suitable for denoising of EEG signal. Finally, a comparison between different filters has been done by two parameters MSE, PSNR. After a comparative analysis, we conclude that a wavelet transform is a useful tool than other filtering techniques in noise removal while sustaining diagnostic information in both the signal.**

Index Terms— Electroencephalography, Adaptive LMS filter, Butterworth bandpass filter, Wavelets, Mean Square Error, Peak Signal to Noise Ratio.

I. Introduction

The electroencephalogram (EEG) signal plays an essential role in diagnosing many neurological diseases for several years. It is used to diagnose various brain disorders such as classification of sleep stages, epileptic seizures detection, brain injuries, Parkinson's, and Alzheimer [1]. EEG is the medical test that records electrical activity in the brain, in which brainwaves are detected by electrodes non-invasively [5]. After recording the brain's neural activity, signal analysis is carried out to investigate many underlying factors that affect brain function. However, EEG signal processing still has some difficulties, as recorded signals are highly non-linear and different for different users; thus, these signals are prone to various types of artifacts [2].

Mainly, there are two sources of artifacts present in the EEG signal: intrinsic and extrinsic. Intrinsic sources include eye blink and eyeball movement, muscle, and cardiac activities, while extrinsic sources include bad electrodes location, not clean hairy leather, electrode impedance, and power line interference [7]. The quality of features extracted from the EEG signal depends on the amount of noise present in the signal used to identify the neurological disorder. Thus artifact removal from the EEG signal is essential in the preprocessing stage [3]. The objective of EEG signal filtering is to preserve the particular frequency of the signal.

In this paper, we have compared different filtering techniques i.e., Adaptive filters, LPF Butterworth filter, Notch filter, wavelets on epileptic EEG signal, and sleep EEG signal. Mother wavelet functions selected are Symlet4, Haar, Daubechies4, Biorthogonal2.6, Coiflets3, Discrete Meyer, Reverse Biorthogonal 6.8, and Reverse Biorthogonal2.8 [4]. The signal is decomposed up to five levels. For comparative analysis, two parameters i.e. MSE and PSNR are used [6]. From the result, it is observed that the wavelet transform is more effective than other filtering techniques in noise removal while sustaining original information in both the signals.

II. Methodology

In this paper, two types of EEG signals viz. epileptic EEG signal and sleep EEG signals, publicly available online on PhysioNet [14], are used for experimentation.

For epileptic EEG signals, 916 hours of continuous scalp EEG data is available with a sampling frequency of 256Hz.

For sleep EEG signal, the database consists of a collection of 20 healthy participants, including 10 males and 10 females for almost 24 hours, sampled at 100 Hz.

Here we have used a single record of the EEG signal from both the datasets, each of 60s duration.

In EEG data analysis, preprocessing is important to eliminate noise from the data to obtain the actual brain signals. At the initial stage of preprocessing, three different filters, i.e., Adaptive filters, LPF Butterworth filter, Notch filter, wavelet transform, have been applied to determine their effectiveness in removing the noise. Notch filter is a special type of band-cut filter that eliminates a single frequency. In EEG denoising, power line frequency can be removed by combining multiple notch filters [7]. LPF Butterworth filter removes baseline changes that occur due to random noise in the EEG recording, affecting the low-frequency range of the EEG signal. These artifacts tend to hide some vital information in the EEG signal [13]. LMS adaptive filtering is more suitable for the removal of artifacts like eye blinks, horizontal eye movements, and vertical eye movements [15]. Wavelet transform is used to study the transient and time-varying EEG signal characteristics because it has outstanding time-frequency localization features.

It has higher frequency resolution and lower time resolution for the low-frequency part, whereas, for the high-frequency part, it has higher time and lower frequency resolution [5].

So we have tested the performances of LMS adaptive filter, Butterworth filter, and discrete wavelet transform.

A. Adaptive Filters:

An adaptive filter is a digital filter that can adapt itself and adjust its coefficients to minimize the error function [6].

The adaptive filter quantizes noise in the input by iteratively adjusting the weights based on the optimization algorithm and subtracts it from EEG signal with artifacts [10][11]. A Block diagram of the adaptive filtering is shown in Fig.1. The input signal is considered as a combination of a clean EEG signal and an artifact source, as given in equation 1.

$$EEG_{N(n)} = EEG_{D(n)} + Noise(n) \tag{1}$$

Where $EEG_{N(n)}$ and $EEG_{D(n)}$ denotes the noisy signal and denoised signal, respectively, and *Noise(n)* indicates the noise signal, which can be any interference according to the artifact to be removed.

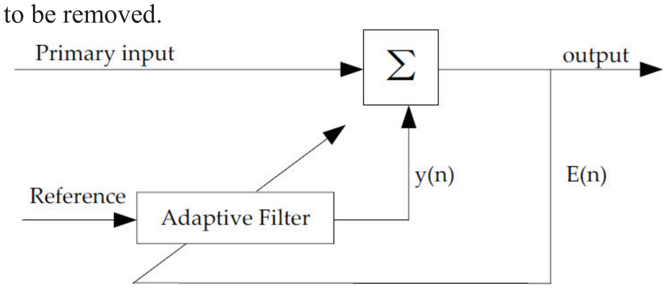


Fig. 1. Adaptive filter system.

B. Digital LPF Butterworth filter:

Firstly, the raw EEG signals are taken. Then the channel is selected from the number of channels, as shown in Fig.2. From the literature, the highest frequency component of interest in EEG signals is the Gamma frequencies, which lie typically in the range of 30 Hz to 80 Hz [8]. Hence the passband edge frequency is selected as 80 Hz. And the typical choice for the stopband edge frequency is chosen as 95 Hz. Passband ripple (Rp) and Stopband attenuation (Rs) are selected as 2 dB and 100 dB, guaranteeing the transition band's optimal filter performance[13].

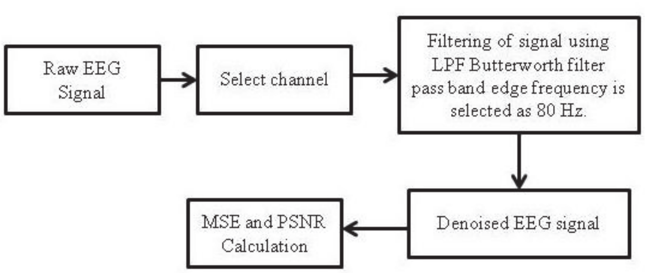


Fig. 2. LPF Butterworth filter

C. Wavelet Transform:

A discrete wavelet transform is used to remove artifacts from the EEG signal [3]. Due to the high tendency to reduce noise while preserving original signal characteristics, Wavelet is considered an efficient denoising method. Commonly used wavelet functions for denoising EEG signals are Symlet4, Haar, Daubechies4, Biorthogonal2.6, Coiflets3, Discrete Meyer, Reverse Biorthogonal 6.8, and Reverse Biorthogonal 2.8 [4].

Wavelet transform is considered as an advanced tool in a non-stationary signal analysis like EEG. When compared with the Fourier transform, wavelet has a useful time-frequency feature [2]. Wavelet transform is transforming the signal with translation and dilation of window function called a Wavelet. Fig.3 gives the process of noise removal using wavelet.

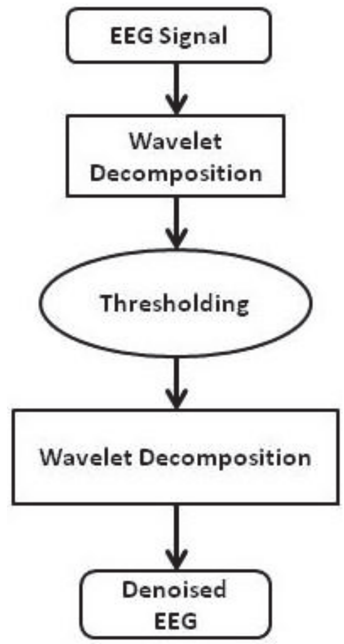


Fig. 3. Filtering process for Discrete Wavelet Transform filter

The wavelet transform based EEG denoising involves the following few steps:

(a) EEG signal wavelet decomposition: Select a Mother wavelet, and decide the decomposition level.

(b) Apply thresholding to the wavelet coefficients.

(c) Reconstruct the clean signal by using the inverse wavelet transform [4].

The transformation is performed after selecting subsets of the scales' j' and the time shift 'k' of the wavelet function $\Psi(t)$.

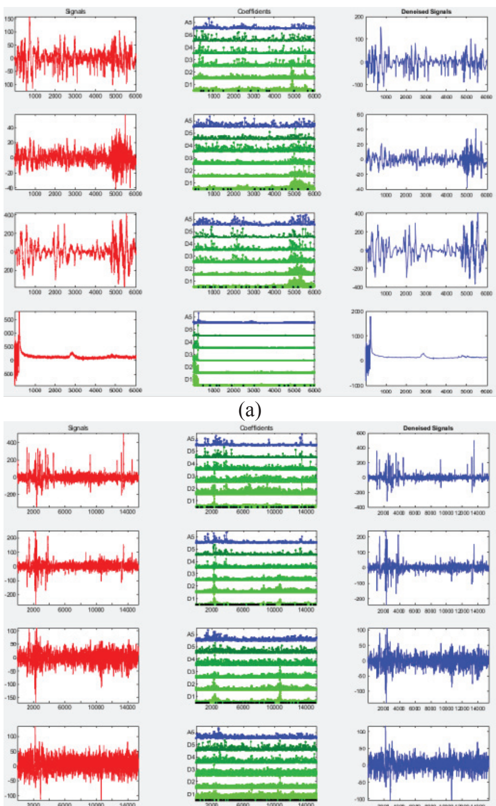
$$\Psi_j, k(t) = 2^{\frac{j}{2}}\ \Psi(2^j t - k) \tag{2}$$

Where j and k are integers. Then the wavelet transform is given by:

$$W_\Psi = < f, \Psi_j, k > \tag{3}$$

It is the inner product of the time-domain signal and wavelet function. Here,we have used biorthogonal 2.6 as our wavelet function.

In this study, the sampling frequency for sleep EEG signal and epileptic EEG signal is 100Hz and 256 Hz, respectively. A five-level decomposition is performed on both the raw EEG signal using wavelet function Bio-orthogonal 2.6 to obtain the coefficient of signals through DWTwhich is shown in fig(4) . A threshold is determined for the signals which is applied on the wavelet coefficients D1, D2, D3, D4, D5 and A5. Where A5 is the decomposition approximation coefficient, and Ds are the decomposition detail coefficients. The effect of the noise on the EEG signals is removed after the threshold coefficients extracted from each stage. The signals is reconstructed using inverse DWT at each step.



(a)
(b)

Fig. 4. (a) 5-level decomposition wavelet coefficients for sleep signal (b) 5-level decomposition wavelet coefficients for epileptic signal

D. Quantitative Evaluation

To evaluate the performance of different filtering techniques, two metrics, Peak Signal-to-Noise Ratio (PSNR) in dB and Mean Square Error (MSE), is calculated [6].

$$PSNR_{dB} = \sum_{i=1}^{N} \frac{p(n)^2}{[q(n)-p(n)]^2} \tag{4}$$

$$MSE = 1/N \sum_{i=1}^{N} [q(n)-p(n)]^2 \tag{5}$$

Here, p (n) denotes the original signal, and q (n) denotes the clean signal; N denotes the number of EEG samples under evaluation. For a better denoising method, it is necessary to have higher PSNR in dB and lower MSE.

III. RESULTS AND DISCUSSION

Denoising the EEG signal plays a vital role in the preprocessing step before further analysis of EEG. At the initial stage of preprocessing, different filters, i.e., Adaptive filters, LPF Butterworth filter, Notch filter, and wavelets, have been applied to evaluate their effectiveness in noise removal. To select the best suitable wavelet function, we have implemented and compared Symlet4, Haar, Daubechies4, Biorthogonal2.6, Coiflets3, Discrete Meyer, Reverse Biorthogonal 6.8, Reverse Biorthogonal2.8, and from table 1, it is observed that wavelet function Bio-orthogonal 2.6 is the best suitable for denoising of EEG signal.

Comparative analysis of filters for epileptic EEG signal and sleep EEG signal is shown in table II and table III, respectively. From Fig. 6, it is observed that, Fig. (e) and (f) appearing more clear than Fig. (g) and (h),but actually, some of the original information content in (e) and (f) is lost due to overlapping spectral between EEG signals and noises. The signals in Fig 6(g) and (h) are the clean signal as wavelet transform gives fair signal resolution in both time and frequency domain as it uses flexible window width. Hence, we can quickly identify a particular pattern embedded in the signals by selecting a good wavelet; therefore, wavelets are more efficient in noise removal than other filters. Statistical analysis is done on both the signals by using two metrics, Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE). Based on the MSE and PSNR values shown in Fig.4and Fig.5., the wavelet Biorthogonal 2.6 function performs effectively compared to other filters. It gives the highest improvement in PSNR up to 46.67 for noise removal.

TABLE I. FILTERING EEG SIGNALS BY DIFFERENT WAVELET FUNCTIONS

Sr. No.	Wavelet Function	Level	Epileptic EEG SIgnal		Sleep EEG Signal	
			MSE	PSNR (dB)	MSE	PSNR
1	Symlet 4	5	0.01374	45.36	0.0104	41.69
2	Harr	5	0.0228	42.95	0.0144	40.08
3	Daubechies 4	5	0.0165	44.37	0.0111	41.52
4	Biorthogonal 2.6	5	0.01064	46.68	0.0087	42.44
5	Coiflets 3	5	0.01304	45.65	0.0107	41.72
6	Discrete Meyer	5	0.01257	45.74	0.0111	41.52
7	Reverse Biorthogonal 6.8	5	0.01344	45.45	0.0108	41.65
8	Reverse Biorthogonal 2.8	5	0.01775	44.15	0.0131	40.82

TABLE II. MSE AND PSNR CALCULATION FOR SLEEP EEG SIGNAL

Filters	LPF Butterworth Filter	Adaptive LMS filter	Wavelet function (Biorthogonal 2.6)
MSE	0.1865	0.0315	0.010
PSNR	34.3362	41.35	46.67

TABLE III. MSE AND PSNR CALCULATION FOR EPILEPTIC EEG SIGNAL

Filters	LPF Butterworth Filter	Adaptive LMS filter	Wavelet function (Biorthogonal 2.6)
MSE	0.0247	0.0249	0.0087
PSNR	38.02	41.24	42.44

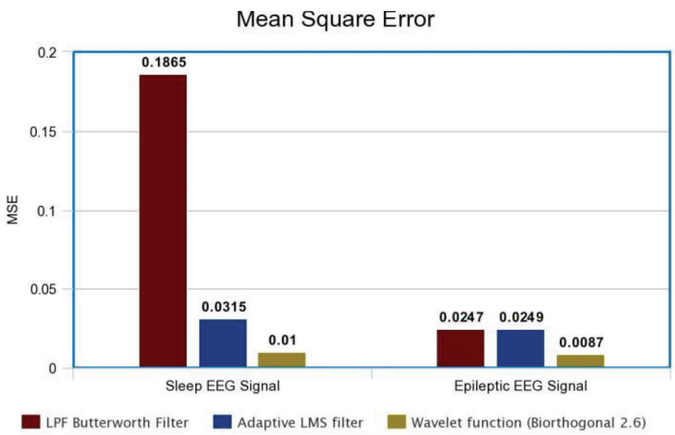


Fig. 5. Mean Square Error of the Butterworth bandpass filter, Adaptive LMS filter and Biorthogonal 2.6 Wavelet

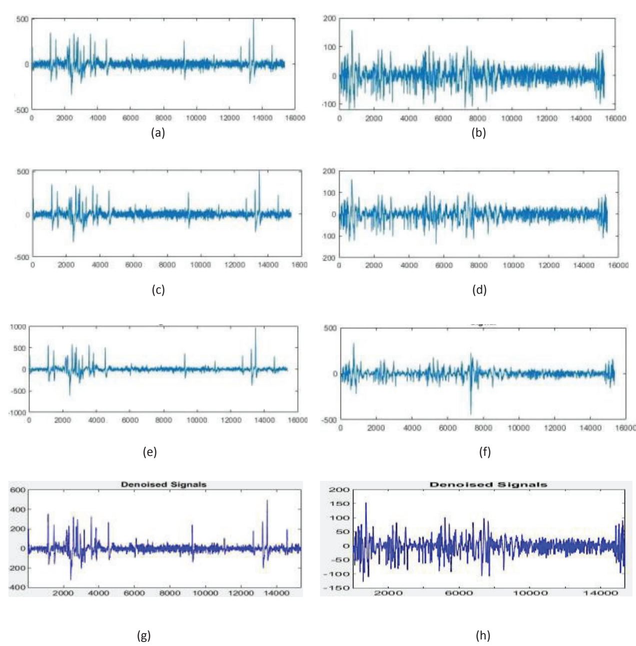


Fig. 6. (a) Raw Epileptic EEG Signal, (b) Raw Sleep EEG Signal, (c) Denoised Epileptic EEG Signal by LPF Butterworth Filter, (d) Denoised sleep EEG Signal by LPF Butterworth Filter, (e) Denoised Epileptic EEG Signal by Adaptive LMS Filter, (f) Denoised Sleep EEG Signal by Adaptive LMS Filter, (g) Denoised Epileptic EEG Signal by Biorthogonal 2.6 Wavelet function, (h) Denoised Sleep EEG Signal by Biorthogonal 2.6 Wavelet function.

IV. CONCLUSION

EEG signals are affected by various artifacts, and filtering the artifact plays a vital role in EEG signal analysis. In this paper, Adaptive LMS filter, LPF Butterworth filter, Notch filter, and wavelets have been implemented to determine their effect on artifact removal. We have shown that All 8 WFs can remove artifacts from the EEG signal competently. But the most capable one to remove noise from both the EEG signals is the Biorthogonal 2.6, as it gives the maximum improvement in PSNR up to 46.68 and 42.44 for noise removal in Epileptic EEG Signal and Sleep EEG Signal, respectively.

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