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A Comparison of Butterworth Band pass Filter and Discrete Wavelet Transform Filter for the Suppression of Ocular Artifact from EEG Signal

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Abstract:

Electroencephalography (EEG) is an electrophysiological monitoring method to record electrical activity of the brain. It is captured by spatially distributed EEG sensors placed on the scalp. The Raw EEG signal is contaminated with various types of artifacts such as power line interference, muscle movement (electromyography artifacts) and eye blinking (electrooculography artifacts). The contaminated EEG may alter the actual result during analyzing stage. To clean the EEG signal different types of filter is used. The aim of this paper is to compare the performance of Butterworth bandpass filter and discrete wavelet transform (DWT) filter when the raw EEG is filtered. To remove electrooculography (EOG) artifact 4^{th} order Butterworth bandpass filter is used. Then DWT is applied to decompose EEG signal into a finite set of subbands. The energy based subband filtering is implemented to separate the lower frequency noise components to clean the EEG signal. The energies of individual subbands of fGn are compared with that of raw EEG to derive the energy based threshold for the suppression of EOG effects. Two factors are used to compare the result of filter on EEG signal; that are signal-to-artifact ratio (SAR) and mean square error (MSE). The experimental result shows that comparatively the DWT is more effective in removing the noise without losing the original information.

Keywords **—bandpass filter, fractional Gaussian noise (fGn), discrete wavelet transform (DWT), energy of sub-band**

I. INTRODUCTION

The quality of electroencephalography (EEG) is degraded by the non-cerebral signal sources are known as artifacts. Among all the artifacts, ocular artifacts are the most prevailing. Ocular artifacts occur through eye movements and blink which generates a signal greater in magnitude than EEG signals, allowing it to travel throughout the scalp, covering and distorting EEG signals [1–4]. In order to achieve higher quality EEG signals, these artifacts must be removed with-out distorting or removing any of the underlying EEG data. There are various methods to control ocular artifacts. One of the modest methods is confining the eye movements and eye blinking of the subject by keeping on a fixed point. Though it is difficult for the subject to perform this task especially for infants or persons with certain disabilities during experiments. Moreover, the effort of performing the task can have a significant effect on the attained EEG data [5]. Another process is to identify and eliminate contaminated trials from the raw data. Contaminated trials are recognized by detecting spike like signals with magnitudes greater than the EEG signal. The removal of these contaminated trials will however lead to loss of EEG data.

In previous research, many simple and complex methods have been proposed for detecting and removing artifacts. The simple signal processing filter, known as Butterworth bandpass filter is used to remove the artifact.The clean EEG signal is easily achieved from raw EEG by applying 4^{th} order of bandpass Butterworth filter.However, this type of filter does not suitable for EEG signal processing because some of the original information are loss during the filtration process. One of the complex method, known as independent component analysis (ICA), makes use of blind source separation [4,6] to determine the original sources (or an estimate of the sources) of a set of signals where each signal is assumed to be a linear mixture of the sources. There exist different assumptions, such as non-Gaussian (NG), non-stationary (NS), spectral density (SD), and hybrid for the static model of the sources [7].ICA has become a popular method in removing artifacts from EEG data. This is accomplished through removal of the component (source) containing the artifact and remixing remaining sources. The disadvantage of ICA is that the components do not necessarily only contain artifact data, but also contains underlying EEG data [2]. Removing the contaminated component will thus lead to loss of EEG data. Addressing this issue, Wang et al. [4] combined ICA and a system identification technique to correct the contaminated component. The system identification technique, auto-regressive exogenous (ARX) uses a short period of clean EEG before the contamination as reference EEG for correction.

Up to now, many methods have been proposed for removing the eye artifacts like: Regression based method(AR) [8,9], Adaptive Filters [10,11], principal component analysis (PCA) [12], and Wavelet Transform (WT) [13].

In regression based method relation between EEG and one or more EOG channels defined with computing propagation factors or transmission coefficient. By estimated proportion of the EOG from EEG we can remove EOG artifacts but this method has a big problem. EEG and EOG can contaminate each other and subtracting EOG from EEG can't remove EOG and also may lose some important information from EEG. In PCA method signals decomposed into uncorrelated, but not necessarily independent based on spatially orthogonality criterion and covariance matrix of signal is considered here and the higher order redundant information may remain in the decomposed components [14].

Wavelet transform is a time-frequency analysis method, and it is suitable for non-stationary signals such as EEG,ECG and EMG. According to the previous studies, Donoho&Johnsone were the first researchers who used wavelet transform for denoising by thresholding wavelet shrinkage [15, 16], it is notable that the majority of the noise removal methods by wavelet transform using a threshold value for artifact removing and reconstructing the signals for having a better result [17,18], but in these methods we may lose some important information during the noise reduction procedure. Hence, in this study we proposed a new method to identify the blink artifacts zone with subband thresholding and removing them by apply energy based threshold.

In this paper, a discrete wavelet transform (DWT) [19] based approach is introduced to separate low frequency artifacts from raw EEG using an adaptive threshold.Thesignal is decomposed using wavelet transform yielding thesubbands. The individual subband is thresholded and added together to obtain the clean signal.Also, this paper aims to shows the comparison when EEG signal filter with 4^{th} order Butterworth bandpass and discrete wavelet transform.

II. METHODS

A. Butterwort Bandpass Filter:

The Butterworth bandpass filter is a type of signal processing filter designed to have as flat a frequency response as possible in the passband. It is also referred to as a maximally flat magnitude filter. In this paper, the 4^{th} order of bandpass Butterworth filter is used. This type of filter is selected because it has linear response compare to others. Due to the frequency of useful EEG is lower than 50Hz, the cutoff frequency used here is 4 to 32 Hz. The delta frequency (below 4 Hz) is rejects because it consider as artifact [20]. Fig.1 shows the block diagram of Butterworth bandpass filtration process. In this Fig., the clean EEG signal is easily achieved from raw EEG by applying 4^{th} order of bandpass

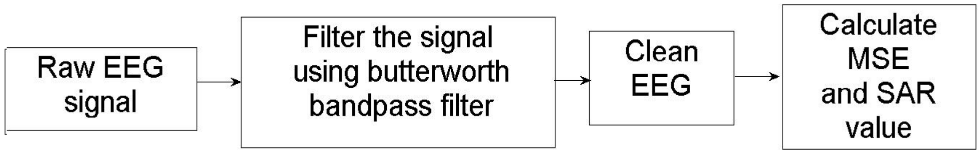

Figure 1. Filtering process for Butterworth bandpass filter

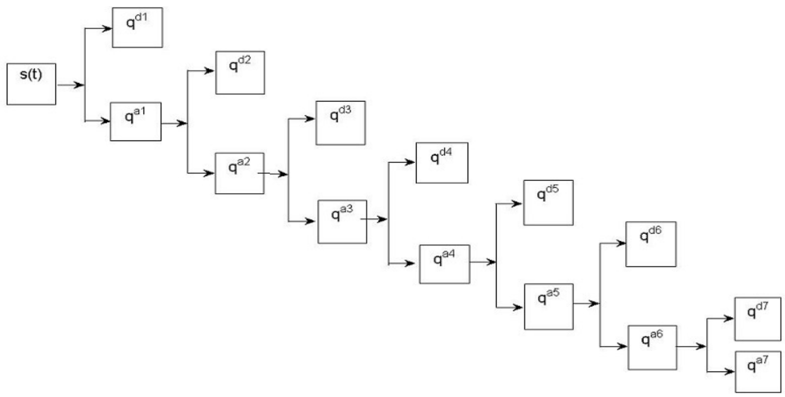

Figure 2. Seven decomposed levels of DWT

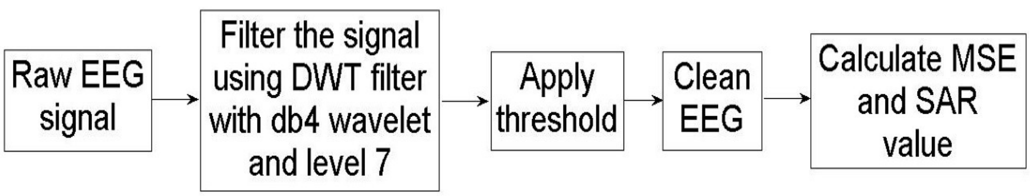

Figure 3. Filtering process for Discrete wavelet transform filter

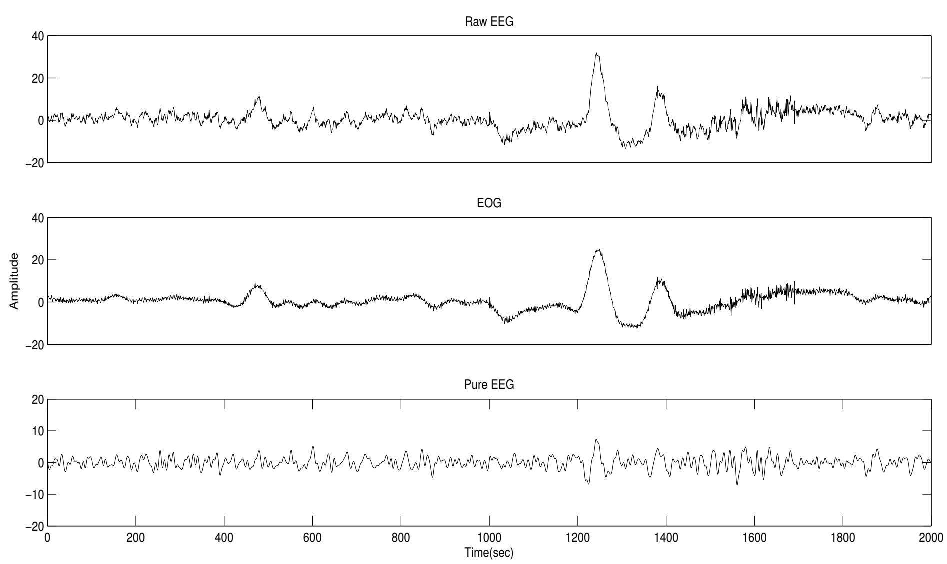

Figure 4. The separation of pure EEG from the raw EEG data by Butterworth bandpass filter

Butterworth filter. Then the performance of the filter is evaluated by the parameters SAR and MSE.

B. Discrete Wavelet transform (DWT):

In discrete wavelet transform, only the lower frequency band is decomposed, giving a right recursive binary tree structure whose right lobe represents the lower frequency band and its left lobe represents the higher frequency band. The seven decomposition level of a signal for the DWT filter is shown in Fig. 2. The frequency band [fm/2:fm] of each detail scale of the DWT is directly related to the sampling rate of the original signal, which is given by fm= $fs/2^L$, where fs is the sampling frequency, and L is the level of decomposition. Here, the sampling frequency is 250 Hz of the EEG signal. The highest frequency that the signal could contain, from Nyquist' theorem, would be fs/2. Frequency bands corresponding to seven decomposition levels for wavelet Daubechies 4 (db4) with sampling frequency of 250 Hz of EEG signals are listed in TABLE I. The signals are decomposed into detail coefficients qd1-qd7 and one final approximate coefficient qa7.

TABLE I
Frequencies corresponding to different levels of decomposition for db4 wavelet filter.

Decomposed signal	Frequency bands (Hz)
q^{d1}	62.5-125
q^{d2}	31.25-62.5
q^{d3}	15.625-31.25
q^{d4}	7.813-15.625
q^{d5}	3.906-7.813
q^{d6}	1.953-3.906
q^{d7}	0.976-1.953
q^{a7}	0-0.976

The wavelet transform (WT) is the decomposition consists of observing the signal at different resolution levels and different translations in time by bandpass filtering [21].The strength of WT based signal decomposition lies in using short high frequency basis functions and long low frequency ones to isolate different characteristics of the signal. Subband signals are reconstructed from the detail and approximate coefficients denoted as $d_1,d_2,\ldots.d_L$ and a_L respectively. The analyzed signal of the channel can be represented as:

$$s(t)=\sum_{b=1}^{L} q_b(t)+q_{L+1}(t) \qquad (1)$$

where, q_b is the b^{th}subband corresponding to the detail coefficient at the b^{th} level and q_{b+1} is the $(L+1)^{th}$subband reconstructed from the approximate coefficient a_b of the channel.

A noise assisted DWT based approach is implemented here to reduce the low frequency noise from single channel EEG. At the end of the decomposition, the signal is represented as

$$\tilde{s}(t)=\sum_{b=1}^{L+1} q_b(t) \qquad (2)$$

where, $\tilde{s}(t)\approx$s(t). The DWT based filtering method of EEG signal is shown in Fig. 3. In this Fig., the clean EEG signal is easily achieved from raw EEG by applying DWT .Then the clean EEG is evaluate by the same evaluation parameter used in bandpass filter. The db4 mother wavelet is choose for this filter.The lower frequency EEG signal of the single channel can be estimated by summing up the lower order subbands as:

$$\hat{s}(t)=\sum_{b=1}^{D} C_b(t) \qquad (3)$$

where, C_b (t) is the b^{th}subband of the channel. Here, the subject is to find the critical (threshold) subband with index D such that the subbands of indices 1,2,3,....,D are responsible for relatively lower frequency pure EEG component.

III. EXPERIMENTAL RESULTS

Dataset:

The real electroencephalography (EEG) data collected from the publicly available Brain Computer Interface (BCI) Competition IV dataset. The EEG data used in this paper retrieve from the BCI Competition 2008 Graz data set B. Technically speaking, this data set 2b consists of EEG data from 9 subjects where all subjects are right-handed, had normal or corrected-to-normal vision. The datasets of each subject consist of five sessions that were recorded on different days, each session comprising ten trials, 2 classes[the motor imagery (MI) of left hand (class 1) and right hand (class2)],six runs,20 trials per run and 120 trials per session. First two sessions contain training data without feedback and the last three sessions is recorded with feedback. All data sets are stored in the General Data Format for biomedical signals (GDF), one file per subject and session. However, only the first three sessions contain the class labels for all trials, whereas the remaining two sessions are used to test the classifier and hence to evaluate the performance. The signal variable contains 6 channels (the first 3 are EEG and the last 3 are EOG signals).The class labels are only provided for the training data and not for the testing data.

In this experiment, we use the downloaded 'B0202T.gdf' filename data for subject 2 and session 2. The GDF file is loaded using the open-source BioSig toolbox (biosig4octmat-2.82) for matlab version. The sampling rate of 250 Hz and the subjects had to imagine the corresponding hand movement over a period of 4 seconds results in 1000 samples per channel for every trial. The cue-based screening sessions consisted of 20 trials per run and 120 trials per session for two classes of imagery. The trials containing artifacts as scored by authorities are marked with 0 corresponding to a clean trial and 1 corresponding to a trial containing an artifact. According to the instruction, we obtained 100 trials as clean trials and 20 trials containing an artifact. Among the clean trials, 51 trials for left hand and 49 trials for the motor imagery (MI) of right hand. Along with contaminated 20 trials, the 9 trials for the motor imagery (MI) of left hand (class1) and 11trials for right handed (class2). We use channel 1, contaminated first 2 trials for real EEG signal for the motor imagery (MI) of left hand.

Experiments:

The sampling frequency of the collected raw EEG signal is 250 Hz. The signal is filtered by Butterworth bandpass at frequency range 4 to 32 Hz. The filtered EEG is considered as pure EEG. The EOG is obtained by subtracting the pure EEG from raw EEG. The result is shown in Fig. 4. In Fig. 4, the top, middle and bottom row presents the raw EEG, EOG and clean EEG signal respectively. This type of filter does not suitable because some of the original information is loss during the filtration process.

To get artifact free EEG the DWT based filter is used. The raw EEG signal and a reference signal fGn are decomposed up to level 7 using db4 mother wavelet. After decompose, we got 8 subbands . The algorithm for DWT [22] to find the index D of the threshold subband for the channel is following:

1) Decompose the analyzing EEG signal together with the fGn into a finite set of subbands using DWT.
2) Calculate the energies of the subbands of fGn and its 95% confidence interval (CI)
3) Compute the energies of all subbands of contaminated EEG. Then find the lowest order subband with energy exceeding the upper limit of CI derived in step 2 say it is the nth subband coefficient. The selected n^{th} (in Figure-7, n = 5) subband coefficient is the starting index to reconstruct electro-oculogram signal.
4) The electro-oculogram artifact is separated by summing up the subband coefficient starting from n^{th} up to the residue of electroencephalography signals.

The determination of threshold subband based on the subband energy is illustrated in Fig.7. After computing the index D of threshold subband (for EEG channel), the pure EEG of that channel is separated using Eq. (3). The completeness of the decomposition is given by the Eq. (2). The subband decomposition of recorded electroencephalography data and fractional Gaussian noise are shown in Fig. 5 and Fig. 6 respectively.

It is observed in Fig. 7 that the 5^{th}subband is the first subband index that exceeds the upper limit of confidence interval and the total number of subbands are 8. The 5^{th}subband coefficient is the starting point of lower frequency components. The electro-oculogram is separated by summing the subband coefficients 5 to 8. By subtracting electro-oculogram from raw electroencephalography, we get the purified electroencephalography that reflects the actual neural activities. The electro-oculogram suppression results for a single channel of recorded

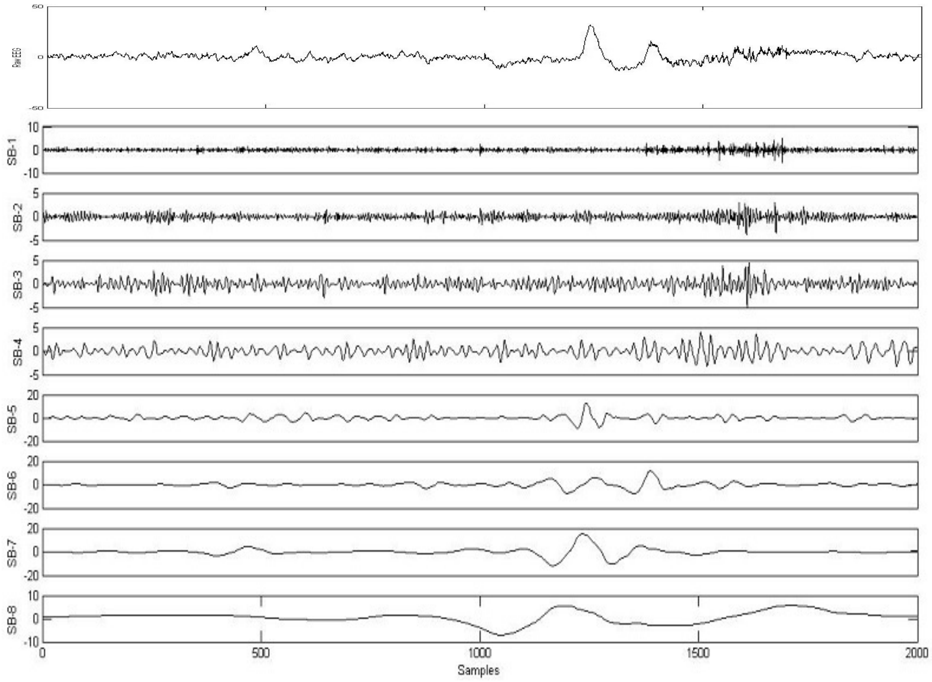

Figure 5. The subband decomposition of raw EEG signal using DWT.

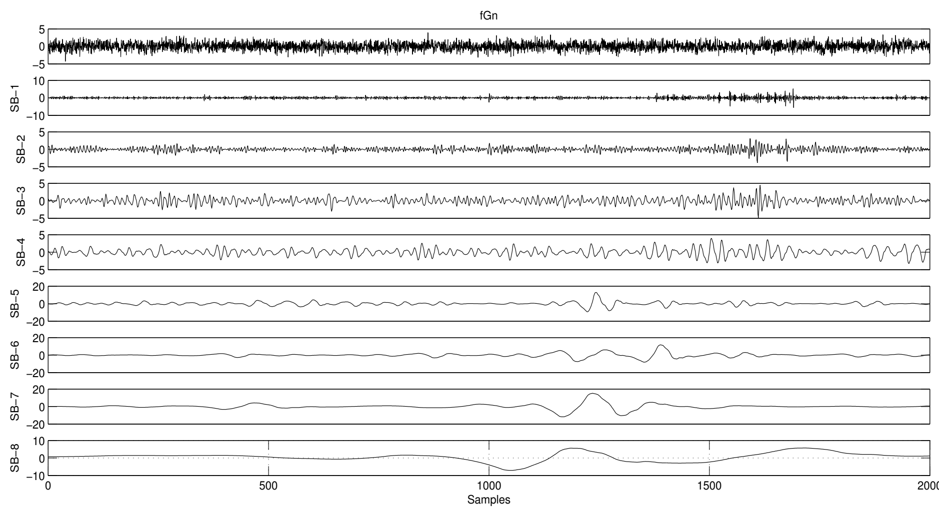

Figure 6.The subband decomposition of fGn using DWT.

electroencephalography are illustrated in Fig.8 in which the separated electro-oculogram and purified electroencephalography signals are shown in the second and third rows respectively. From Fig. 8, it is observed that the purified EEG signal contains more original information although the artifact has cancel out. It is apparent that using Butterworth bandpass filter for artifact correction, underlying EEG or low frequency cerebral data may be lost. In order to reduce the data loss DWT method is used. Fig. 9 depict the raw EEG and clean EEG for the two methods. From this Fig., it is observed that the DWT baesd method is best for reduce the EOG from raw EEG without cutting the information and assist to get clean EEG. The electro-oculogram artifacts are compared in Fig.10. From this Fig., it is practical that the butterwothbandpass filter cut the original information with EOG which is absent in DWT.

Performance metrics:

In order to determine whether the method is successful at removing ocular artifact from EEG, the performance is assessed using signal to artifact ratio (SAR) and mean square error (MSE).

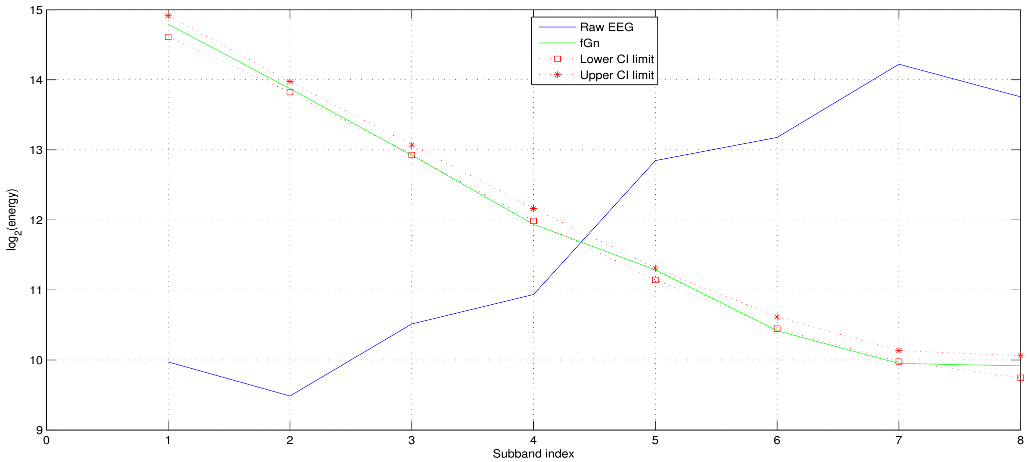

Figure 7. The selection of threshold subband index of 5 EEG channel based on the subband energy of fGn. The 5thsubband exceeds the upper boundary of CI and hence the 5th one of EEG signal is selected as the highest order subband index D to represent the pure EEG signal.

Figure 8. The separation of pure EEG from the contaminated data using energy based subbandthresholding.

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