Ocular Artifact Detection and Removing from EEG by wavelet families: A Comparative Study

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Abstract
The Electroencephalogram (EEG) is a biological signal that represents the electrical activity of the brain. Biological artifacts like ocular artifact (OA) are one of the main interferences in EEG recordings. Eye blinks and movements of the eyeballs produce a signal known as electrooculogram (EOG) that these are 10 to 100 times stronger than the EEG signal. Due to the frequency range of EEG signal and OA which has overlapping with each other, identify and removing of the EOG artifacts are one of the main challenges for researchers, because an incorrect denoising may lose some of the important information of EEG signals. In this context, our aim is to propose a technique based on wavelet transform for accurate identification of the blink artifact zone and removal of EEG signals. We propose using absolute value of signal reconstructed details for blink zone detection and the efficiency of wavelet families to remove the blink artifact which is evaluated by calculating the mean squared error (MSE) between denoised and clean EEG signals and comparing with the results before and after artifact removing show that db7, sym7, coif5, rbio1.5 and dmey at 4th level are preferable and effective in blink artifact zone detection and db7, coif5, dmey, db5 and db9 respectively provide the best result for blink artifact removing with minimum loss important information.
Keywords: EEG, EOG, OA, Wavelet transform, MSE

Introduction

Electrical recordings from the surface of the brain or even from the outer surface of the head represent that there is continuous electrical activity in the brain that are called brain waves, and the entire record is called an EEG (electroencephalogram).

The intensities of brain waves recorded from the surface of the scalp range from 0 to 200 microvolts, and their frequencies range from once every few seconds to 50 or more per second. The character of the waves is dependent on the degree of activity in respective parts of the cerebral cortex, and the waves change markedly between the states of wakefulness and sleep and coma. [1]

The EEG is typically has rhythmic activity and five major brain waves distinguished by their different frequency ranges. These frequency bands from low to high frequencies respectively are called delta (δ) (0.5–4 Hz), theta (θ) (4–8 Hz), alpha (α) (8–13 Hz), beta (β) (13–30 Hz), and gamma (γ) (> 30 Hz).[2]

Analyses of the EEG signals are very important in human brain research, disease diagnosis such as finding of epileptic seizure, Psychiatric disorders, and other clinical disorders. Unfortunately always some of signals with no cerebral origin that they called Artifacts, effect on EEG signals. Because of the amplitude of artifacts can be quite large relative to the size of amplitude of the cortical signals, it may create some problems in EEG interpretation. Therefore we need signals without artifacts. Some of the more common types of artifacts are: eye artifacts like eye movements or eye Blinks, ECG (Cardiac) artifacts and EMG (muscle activation) artifacts.

We mentioned three types of biological artifacts but eye movements that produce a large electrical potential and known as Electrooculogram (EOG) are very important among EEG artifacts because eye movements cause a change in the electric fields that surrounds the eyes and this distorts electric fields over the scalp. [3]

Up to now, many methods have been proposed for removing the eye artifacts like: Regression based method (AR) [4,5], Adaptive Filters [6,7], principal component analysis (PCA) [8], independent component analysis (ICA) [9] and Wavelet Transform (WT) [10].

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 [11]

Independent component analysis (ICA) for the separation of EOG from EEG signals has been used. In this method assume that the recorded potential on the scalp is composed of a weighted sum of the potential sources, so EOG and EEG can be separated into independent brain sources. This method requires asynchronous analysis and collected data processing from adequate channels. [12]

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 [13, 14], 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 [15,16], 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 high accuracy and removing them by using wavelet approximation levels to get the best result and minimal loss for important information about the original EEG signal. The efficacy of the wavelet families for identification of the blink artifact zone and removing them from EEG signal also has been studied.
An EOG reference channel has been used to identify and remove noise from an EEG signal in most of the studies. But in some cases the EOG channel for analyzing may not be available, therefore in our study due to using EEG signal characteristic it is not necessary to use EOG channels.

2. Materials and methods

2.1 Wavelet transform

Wavelet analysis is a technique that is capable of measuring time and frequency variations of a signal simultaneously with functions called wavelets.
Wavelets are oscillating amplitude functions of time that must satisfy several conditions: a wavelet ψ is a function that is zero average over time and has unit energy. The amplitudes of a wavelet have large fluctuations within a designated time period and extremely small values outside of that time while being band-limited in terms of their frequency content. This property allows them to be localized in time and frequency [17]. The wavelet chosen to perform a wavelet transformation is called the mother wavelet. During a wavelet transformation the signal of interest gets transformed into being presented that can demonstrate frequency content at different points in time. Scaling or dilation can be used to stretch or compress the wavelet and translation is used to move the wavelet to different positions in time. A wavelet family is the set of all scaled and translated wavelets [17]. Dilating with a scaled parameter s and translating by u results in (10).

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{10}$$

Stretching a wavelet makes it less localized in time, but refocuses its bandwidth towards a lower frequency range.
The continuous wavelet transform (CWT) of a signal f can be calculated using (11) where * indicates the complex conjugate. Varying the values for s and u results in an infinite number of combinations that can be used to decompose the signal, f. For the CWT to be realistically implemented, the wavelet used must meet the admissibility condition in equation (12) [18].

$$\mathrm{C}(\tau, \mathrm{s}) = \frac{1}{\sqrt{s}}\int_t f(t)\psi^*\left(\frac{t-u}{s}\right)dt \tag{11}$$

The CWT is very inefficient because of the redundancy that occurs when displaying closely spaced time points [17]. A much more computationally efficient approach is the use of the discrete wavelet transform (DWT), which was developed by Mallat [19]. The Discrete Wavelet Transform (DWT) means, choosing subsets of the scales ‘j’ and positions ‘k’ of the mother wavelet ψ(t) in equation (12).

$$\psi_{jk}(t) = 2^{\frac{j}{2}}\psi(2^j t - k) \tag{12}$$

The efficacy of this technique occurs because the
DWT coefficients are a subset of the CWT coefficients based on powers of two [17]. Knowing only the values of the DWT coefficients, the waveform can be perfectly reconstructed.
In implementation, the DWT performs even better because the waveforms are already digitally sampled and have finite duration so the number of coefficients is limited [17]. The DWT produces as many wavelet coefficients as there are samples in the original signal by using a filter scheme shown in Figure 1.1

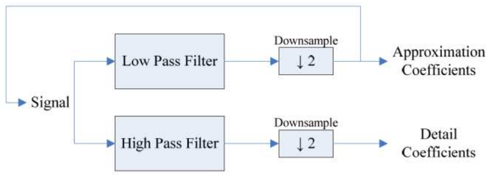

Figure 1.1 – DWT Decomposition Scheme

The original signal is convolved with a low and high pass filter whose impulse response is determined by the wavelet chosen. The output of each filter produces the same number of samples as the original signal, so both outputs are down sampled by 2 resulting in the approximation and detail coefficients each with half the number of points as the original signal. The coefficients represent a correlation between the signal of interest and wavelet chosen at different scales and during translation. Because all of the coefficients are preserved, the original signal or any level of decomposition can be reconstructed using a filter scheme similar to decomposition shown in Figure 1.2.

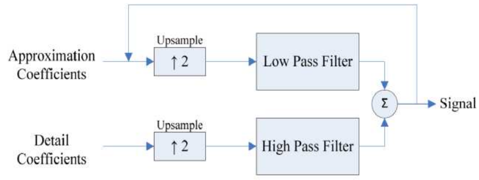

Figure 1.2 - DWT Reconstruction Scheme

2.2 Dataset

The EEG data that it used in this paper retrieved from the BCI Competition 2008 Graz data set B. This data set consists of EEG data from subjects were right-handed, had normal or corrected-to-normal vision.

All volunteers were sitting in an armchair, watching at screen monitor placed approximately 1m away at eye level. First two sessions contain training data without feedback (screening), and the last three sessions were recorded with feedback.

Three bipolar recordings (C3, Cz, and C4) were recorded with a sampling frequency of 250 Hz. The recordings had a dynamic range of 100 µV for the screening and 50 µV for the feedback sessions. (The data with feedback used in this study). They were band pass-filtered between 0.5 Hz and 100 Hz, and a notch filter at 50 Hz was enabled and all data sets are stored in the General Data Format for biomedical signals (GDF).

The Electrooculogram (EOG) was recorded with three monopolar electrodes. (Fig.2). The cue-based screening paradigm consisted of two classes, namely the motor imagery (MI) of left hand and right hand. For the three online feedback sessions four runs with smiley feedback were recorded (Fig.2.1), whereby each run consisted of twenty trials for each type of motor imagery. At the beginning of each trial (second 0) the feedback (a gray smiley) was centered on the screen. At second 2, a short warning beep (1 kHz, 70 ms) was given. The cue was presented from second 3 to 7.5. Depending on the cue, the subjects were required to move the smiley towards the left or right side by imagining left or right hand movements, respectively.

During the feedback period the smiley changed to green when moved in the correct direction, otherwise it became red.

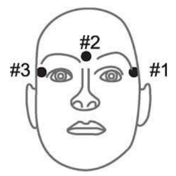

Fig.2 Electrode of the three monopolar EOG channels.

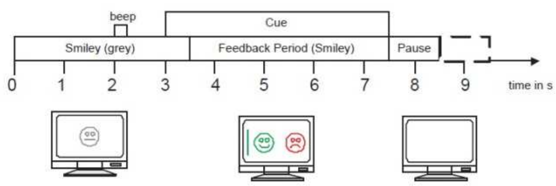

Fig.2.1 Sessions with smiley feedback.

2.3 EEG simulation

The EEG recordings usually are contaminated by biological artifacts like ECG, EOG and EMG signals that originate from non-cerebral origin.

The eye, facial muscles and brain activities have physiologically separate sources [20] so we can consider a clean EEG (Fig.3.a) (EEG without artifact) and a blink artifact signal (Fig.3b) separately as the same length (750 samples equals 3s) and make an EEG signal with EOG artifact by equation 1 (fig. 3c).

$$EEG_{test} = EEG_{clean} + k \times EOG_{clean} \quad (1)$$

Where k represents the propagation factor from the EOG to the EEG signal. In this study, it was supposed that the propagation factors of EOG to three channels (C3, Cz and C4) were 0.075, 0.0375 and 0.08 respectively.

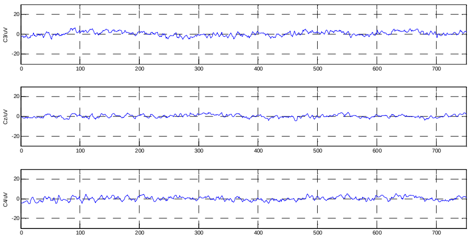

Fig3.a. Clean EEG

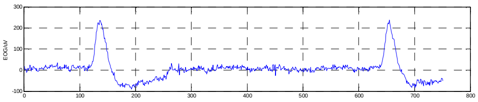

Fig3.b Blink artifact

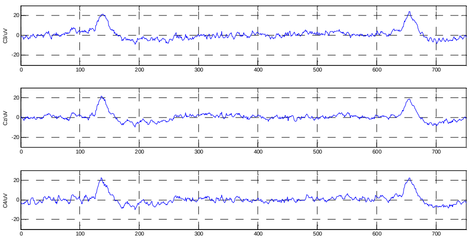

Fig3.c. EEG contaminated with EOG constructed by equation 1

3. Automatic Identification of OA Zones

By analyses of the frequency spread of the EEG data that contained the ocular artifacts, researchers found that the difference in the frequency of the spikes which caused due to the eye blinks and the EEG signal could be used along with a simultaneous recording of the EOG to detect and remove these artifacts. But correlation of the EEG and EOG is futile, especially because of the inherent corruption of EEG data by the restraint on the users' eye movements and blinks. [21]

In [9,10], Haar wavelet is used to decompose the recorded EEG Signal to detect the exact moment when the state of the eye changing from open to close or close to open. Decomposition of the EEG data with the Haar wavelet results in a step function with a falling edge for a change in the state of the eyes from open to close and a step function with a rising edge for a change in state of the eyes from close to open. The same technique is used to detect the ocular artifacts zones in the contaminated EEG.

In this paper we present a new method for OA zone detection by using decomposition the EOG artifact signal in some levels and using the absolute value of the reconstructed signal.

After studying on different wavelet families and analyses the results, these families selected for OA zone detection: db7, sym7, rbio1.5, coif5 and dmey.

First of all we decomposed the signal in various levels and the best result obtained when the decomposition of EEG containment with EOG occurred in 4th level. In the next step we decompose the EEG signal in 4 levels by several wavelet families and used absolute value of reconstructed detail at level 4 for observing OA zone in EEG signal. In order to represent blinking zone more accurately, we set a manual threshold value for absolute detail in which the samples exceed this threshold considered 1 and 0 vice versa. OA zone detected by several wavelet families is shown in Fig.4 in which the best results belong to db7, sym7, coif5, rbio1.5 and dmey.

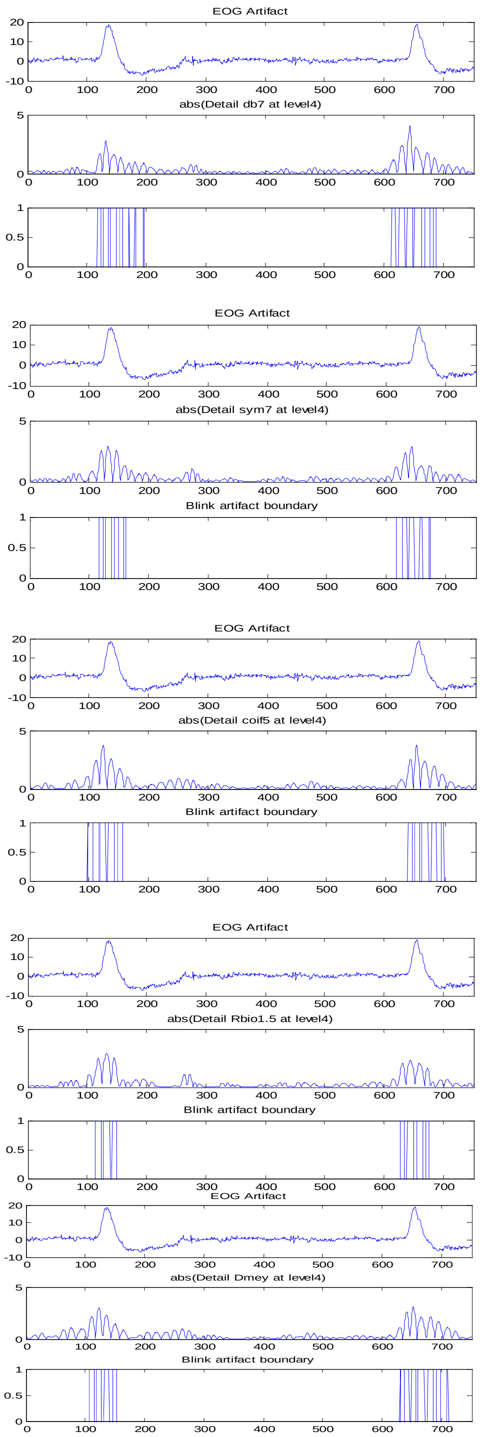

Fig.4 a) EOG artifact signal, b) Eye blinks zone detection by the absolute value of wavelet families reconstruction at 4th level, c) OA zone detected after set a manual threshold

4. Artifact removing

For blink artifact removing we consider clean EEG from 3 channels C3,Cz and C4 and we made EEG signal that contaminated by EOG artifact according to equation1 which were shown in Fig.5.

After making test signal by equation1 and detecting the accurate blink artifacts zone so we proposed removing method which will be explained as follows:

We used to transform to decompose the contaminated EEG signal into several subbands. After analyses the statistical characteristics of blink zones in each level, we found out that the approximation at 4th level has the most similarity to references blink artifacts.

We considered just blink artifact zone in approximation level that it identified in the previous step and by removing them from contaminated EEG the result will be a signal without blink artifact. Unlike other methods in which all artifacts removed from EEG signal, in our method due to using blink artifact zone in approximation level for denoising EEG, all important information preserved.

MSE performance is used for quantifying and assess the denoising method effect [22]. MSE was calculated as follows:

$$MSE = \frac{1}{N}\sum_{n=1}^{N}[(\mathrm{S(n)} - \mathrm{D(n)})^2]$$

Where S(n) is the clean EEG, while D(n) is the denoised EEG signal, and N is the number of sampling points. Smaller values of MSE means that the denoised EEG is more closed to clean EEG.

MSE values of 28 wavelet families before and after EOG artifact removing are shown in table1.

According to the MSE values of the wavelet families, top 5 families for EOG artifact removing are respectively: db7, coif5, dmey, db5 and db9.

Blink artifact removed by using db7 for C3, Cz and C4 channels are shown in Fig.5 with red lines.

	Wavelet family	MSE before denoising	MSE after denoising
1	Db4	21.3165	0.35589
2	Db5	21.3165	0.30767
3	Db6	21.3165	0.33426
4	Db7	21.3165	0.30407
5	Db8	21.3165	0.32732
6	Db9	21.3165	0.30796
7	Sym5	21.3165	0.33197
8	Sym6	21.3165	0.31366
9	Sym7	21.3165	0.32177
10	Sym8	21.3165	0.32707
11	Coif2	21.3165	0.34158
12	Coi3	21.3165	0.30944
13	Coif4	21.3165	0.32482
14	Coif5	21.3165	0.30451
15	Bior3.1	21.3165	0.46705
16	Bior3.3	21.3165	0.34779
17	Bior3.5	21.3165	0.33200
18	Bior3.7	21.3165	0.30830
19	Bior3.9	21.3165	0.31054
20	Bior4.4	21.3165	0.31058
21	Bior5.5	21.3165	0.31772
22	Bior6.8	21.3165	0.32723
23	Rbio1.3	21.3165	0.35842
24	Rbio1.5	21.3165	0.34948
25	Rbio2.8	21.3165	0.33266
26	Rbio3.9	21.3165	0.31626
27	Rbio6.8	21.3165	0.33056
28	Dmey	21.3165	0.30713

Table1. Wavelet families MSE value before and after EOG artifact removing

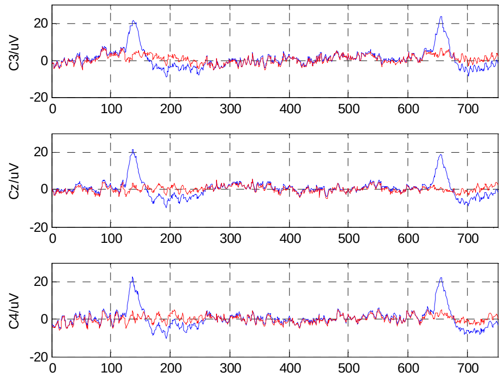

Fig.5 Blink artifact removing by db7 from C3, Cz, C4 channels

4.1 Application to real EEG

In this section after removing the blink artifact of simulated EEG signal, the proposed method was employed to a real corrupted EEG data.

EEG data retrieved from the BCI Competition 2008 Graz dataset A. This data set consists of EEG data from 9 subjects. The cue based BCI paradigm consisted of four different motor imagery tasks, namely the imagination of movement of the left hand, right hand, both feet, and tongue.

Twenty-two Ag/AgCl electrodes were used to record the EEG. All signals were recorded monopolarly with the left mastoid serving as a reference and the right mastoid as ground. The signals were sampled with 250 Hz and bandpass-filtered between 0.5 Hz and 100 Hz. The sensitivity of the amplifier was set to 100 µV. An additional 50 Hz notch filter was enabled to suppress line noise.

Twenty-two EEG channels, 3 monopolar EOG channels were recorded and also sampled with 250 Hz. They were bandpass filtered between 0.5 Hz and 100 Hz (with the 50 Hz notch filter enabled), and the sensitivity of the amplifier was set to 1 mV. The EOG channels are provided for the subsequent application of artifact processing methods [23].

The data in this experiment were from subject 1 and we choose 3 channels EEG over P3, P4, Cz and EOG data, as shown in Fig.6. It is obvious that the blink artifact is removed perfectly from EEG, and it proves that our propose method is also effective and powerful in real contaminated EEG recordings. It provides a novel preferable method for preprocessing of EEG data.

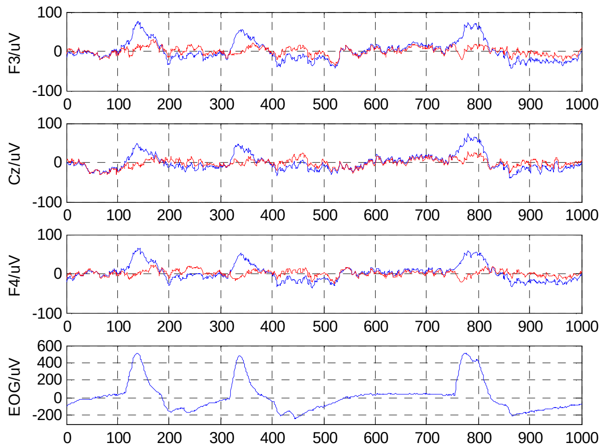

Fig.6 Blink artifact removing from real contaminated EEG

Conclusion

One of the important problems in EEG data analysis for disease diagnosis, brain research and etc is biological artifacts and EOG which is one the most significant artifacts compared to others. For removing of EOG artifact many methods have been proposed based on wavelet transform but loss of EEG data information and remnant artifact in the samples are the main problems in these methods therefore main reasons for these events are incorrect detection of the artifacts zone and inappropriate uses of wavelet families.

In this paper we proposed a novel method for accurate EOG artifact zone detection and we compared different wavelet families for detection and removing of blink artifact.
Some comparisons are performed between wavelet families for removing the blink artifact in simulated and real EEG signals and that demonstrated which of these families are more appropriate. In fact, the results of the experiment indicate that the db7, sym7, rbio1. 5, coif5 and dmey have the best result among wavelet families for blink artifact zone detection. MSE performance demonstrated that the db7, coif5, dmey, db5 and db9 provide the best result for blink artifact removing respectively. It is concluded that the proposed method has less complexity and is easier to remove the EOG artifact by wavelet decomposition and this method is a very efficient technique which removes EOG artifact with high efficiency and prevent the loss of EEG important information in clinical and engineering analysis.

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