Received: 4 March 2024 | Revised: 28 May 2024 | Accepted: 5 July 2024 | Published online: 12 July 2024

RESEARCH ARTICLE

Journal of Data Science and Intelligent Systems
2024, Vol. 00(00) 1–5
DOI: 10.47852/bonviewJDSIS42022757

A Composite Filter Based Approach for Artifact Elimination and Segmentation of EEG Signal for Application in Brain Computer Interface

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Abstract: Electroencephalogram (EEG) signal is one of the important bio signals which can characterize different states of action. These signals are often contaminated with different artifacts. Dominant artifacts are baseline wandering, power line and eye blink noise. The frequencies of these artifacts overlap with the frequencies of the EEG sub bands and create a major challenge for analysis. In the present paper, a computationally simple, robust to noise and accurate EEG segmentation algorithm is developed for all dominant noise elimination from the EEG signal. The proposed method uses moving average and Discrete Wavelet Transform filtering techniques. The novelty of the present work lies in the use of moving average and DWT filter which eliminates the major noises without affecting the properties of the signal and subsequent sub band segmentation without additional signal processing. The choice of db4 as mother wavelet reduces the computational time and complexity. The method has been tested on real time signals acquired from thirty individuals of varying age group. Comparative plot of acquired and clean electroencephalogram justifies the applicability and potentiality of the method for various applications including brain computer interface. Relative Root Mean Square Error (RRMSE) between the acquired and filtered signal is only 0.14 ± 0.03 which reveals that the filtering stage did not had any loss to the vital signature properties. The earlier reported literatures have the best possible value of RRMSE to be 0.42 ± 0.00 which is quite a distant apart from the present result. The proposed algorithm can be a suitable option for major artifact elimination and EEG segmentation in low-cost single-channel EEG systems because of its (a) computationally efficiency; (b) filtering contaminated EEG signals in millisecond time resolution; (b) automatic, requiring no human intervention; (c) non-invasive, preserving unaltered EEG intervals without contamination; and (d) low-complexity, requiring no artifact reference.

Keywords: baseline wandering artifact, electroencephalogram, eye blink signal, discrete wavelet transform, moving average filter, power line interference artifact

1. Introduction

The ageing of the population and the devastating effects of many chronic illnesses are currently the main factors contributing to the rise in disability in our society. Technology intervention in the healthcare sector has now become necessary to battle the results on a daily basis [1]. Over two billion individuals worldwide will require at least one assistive technology product by 2030, according to recent World Health Organization (WHO) reports. As a result, the development of various Brain-Computer interfaces (BCIs) has received a great deal of scholarly interest in recent years. In order to help patients with neurological or physical disorders, modern BCIs can now process human-defined instructions that are communicated via standard bio-signals and other human reactions [2]. However, the most practical method of interacting with BCIs for treating illnesses and other applications associated with acute muscular movement is to analyze the patient's brain signal [3].

EEG or electroencephalogram is the important bio signal which can be recorded from the surface of human body for estimation of the physical as well as mental condition. EEG is applied to detect abnormalities in the activity and operation of the brain which can be related to some brain related disorders. The measurements from EEG signal can be applied to rule out or confirm various mental conditions, mental stress, seizures, brain tumour, head injury, encephalitis, stroke, encephalopathy, memory problems and sleep disorders along with alcohol or drug abuse. While a person is in a coma, the level of brain activity can be judged from EEG signals. The most significant characteristics of this signal are its signature property which varies from individual to individual even at the same physical or mental state. EEG based analysis is gaining importance in present world because it has the potential of an emerging technique to control several devices such as wheelchair for disabled persons and also for normal healthy individuals in driving an automated vehicle and for controlling robots. It has a diverse application in Brain Computer Interface (BCI) applications and for gaming console. In all these applications, tracking of eye blink movements is an important aspect. The accuracy of the above applications depends upon the effectiveness of artifact elimination and detecting the eye blink movements. The eye blink movements contain a rich source of information which might be applied for other applications, but these are considered to be additional artifacts for the present study. Hence these eye blink signals are essential to be removed in addition to the power line and baseline noises from the acquired EEG data. The clean EEG signal will have various signature properties which can be a valuable source for real time BCI based applications. This inherent property makes it superior than the other bio signals and hence modern day researchers are focusing on EEG signal.

2. Literature Review

Motion artifacts creates abnormalities in the EEG signal can be caused by a number of things, including incorrect electrode contact with the scalp and head movements [4]. For a number of EEG signal-based pattern classification tasks, including brain–computer interface (BCI) [5, 6], seizure detection [7], Alzheimer's disease detection [8], biometrics, health monitoring [9], emotion recognition, and stress detection [10], the motion artifact must be removed. The existing methods for the study of BCI and human emotions involve analysis of EEG signals which are acquired from the human scalp. EEG signals are contaminated by the artifacts arising from power line and baseline interferences, eye blinks, cardiac activity and muscle activity during recordings. Baseline noise mainly arises due to the respiration signal of the subject [11]. Eye blink artifact arises due to the closing and opening of the eye ball, which is beyond the control of the acquisition set up. Artifacts related to cardiac and muscular movements are also present in almost all the recorded data strips. It is very much essential to remove the blink artifacts since these noises can lead to faulty analysis.

Power line noise is a common noise component which is present in all the records. Power line artifact arises due to power line connection to the acquisition set up and is normally having a fixed frequency. Use of median filter to eliminate power line and baseline artifacts from ECG signal has also been reported in literature [12]. Although median filter can be used to eliminate the power line noise from the recorded signal, the filter introduces an additional delay into the processing cycle. Moreover, the use of higher order Butterworth filter is available in the literature [13]. But this filter gives the best result for EEG signal. On the other hand, some researchers have applied the technique of moving average filtering for eliminating power line noise from the physiological signals. This method is relatively faster than other filtering methods and is thus suitable for real time applications.

Researchers have also tried to filter out the artifact caused due to eye blink using linear filters having the cut-off frequency chosen according to the noise signal. But this method does not satisfactorily perform because of the fact that the EEG signal is non-stationary in nature along with the non-periodicity of the noises. The overlapping of the different waveforms of EEG with that of eye blink signal is the major challenge with regard to its elimination. One of the normal methods to eliminate ocular artifact is regression-based method. However, there is a need of recording the electrooculography channel (EOG). Several time domain techniques and filtering provide substantial loss of valuable data pertaining to the condition of brain which might lead to faulty conclusion. Use of Principal Component Analysis (PCA), Independent Component Analysis (ICA), wavelet denoising and automated denoising [14] for elimination of artifacts have been reported in literature. ICA is considered to be a very accurate method of eye movement noise removal, but the method requires manual intervention for the identification of the independent components. The method of ICA can be applicable only if the pre-processing of the signal is properly executed. Component identification can be done using linear trends, spectral temporal maps, data improbability and Kurtosis, but these methods require an additional EOG signal record for reference. Thus it becomes a time consuming and unsuitable process. Some researchers have used Laplacian filtering technique for removing the artifacts. These filters are used to enhance the electric activities which are located closer to an electrode, while suppressing the components having an origin outside the skull. But overall, the common EEG component gets attenuated from the recording channels so as to enhance the quality of the signal [15]. Researchers have used the joint-resolution feature of wavelet transform (WT). The multi resolution property of WT in time-frequency plane is required for the extraction of detail and approximation coefficients of the signal. This decomposition is not possible using transforms like fast Fourier transform and short time Fourier transform. Different mother wavelet functions have been used in the literature for extraction of different approximate and detail coefficients using discrete wavelet transform and it has been observed that the Daubechies family generates the best possible results with EEG signal [16]. Kurtosis and modified entropy based methods have been reported to detect the independent eye blink components and subsequent denoising of the components using wavelet transform based technique [17].

Activity related to eye ball movements can be directly measured from the Electroocoulogram (EOG), by placing leads near the eyes. Although these measurements can give the estimation of eye ball movements, but are often corrupted due to the presence of EEG signals. Thus the method of subtraction of the EOG is, therefore, not a viable solution. Use of regression based methods has been reported for eliminating eye blink artifacts. The disadvantage of using this method lies in the requirement of a good reference EOG channel. PCA is not capable enough to separate out EOG artifacts completely from the EEG records if both the amplitudes are comparable. The application of PCA requires the condition that the components should be spatially orthogonal. In reality, the artifacts will never be orthogonal to the EEG source spatially. Therefore, it is not possible to separate the mixed signals into EEG and EOG components using PCA. It is reported in the literature that joint application of PCA along with source modeling provides a better result for artifact removal. Still there is a requirement of calibration data and inverse source solutions of EOG and EEG for improving accuracy of this method. Automatic method of EOG artifact elimination using blind component analysis and separation was also used along with the help of one additional EOG electrode. But the use of median filter does not give equally good result for EEG signal because of the non-stationary and feeble nature of EEG signal. In view of the above literatures, it is clear that the choice of filtering technique is very crucial for proper elimination of major artifacts from EEG before further analysis. The above methods either introduces non linearity in the output and distorts the signal component to a certain degree on one hand while the other techniques involved causes a low of few data points near the cut off frequencies which becomes a challenge from the viewpoint of clinical information content. This initiates the use of such a filtering technique which does not distort the signal components and retain the vital signature properties of the original signal. This leads to the use of moving average and discrete wavelet transform based filtering techniques for the present work.

However the present authors feel that although the EOG signal embedded in the EEG signal is a valuable source of information regarding the eye movements; it can be removed from EEG using a composite filter. In the present work, the EEG signal is extracted from the recorded signal and EOG signal is treated as one of the artifact. The present work focuses on the following steps:

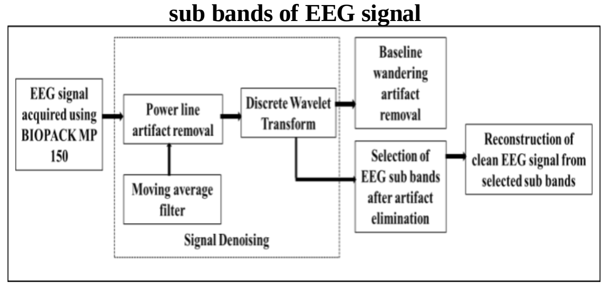
i. Recording of EEG signal using six electrodes.
ii. Elimination of power line artifact.
iii. Elimination of high frequency artifact.
iv. Elimination of baseline wandering artifact.
v. Elimination of eye blink artifact.
vi. Selection and reconstruction of coefficients for obtaining clean EEG.

Therefore, this study which is the first of its kind, attempts to eliminate all major artifacts using a composite filter and segments the clean EEG into its constituent sub bands in order to fill the literature gap left by previous studies. The novelty of the present work lies in the application of moving average filter along with DWT filtering for noise elimination and signal segmentation of the raw EEG. Most of the available literatures use DWT to segment the EEG signal along with other higher order filters for power line and baseline artifact removal. This introduces signal loss and additional delay in the filtering process. On the other hand, few of the reported literatures use higher order Butterworth and Chebyshev filters for noise elimination, but they do introduce loss of vital signature properties of the clinical signal. Use of the unique averaging technique for removal of eye blink artifact is the added novelty for the present work which, to the best of our knowledge is not available in the literature.

3. Methodology

The proposed algorithm mainly comprises of three different sections which are denoising of acquired EEG signal, selection of specific sub bands of EEG using composite filters and identification of different EEG sub bands along with their reconstruction for application in BCI applications. In the signal denoising stage, power line artifact and baseline wandering artifact are eliminated by using discrete wavelet transform and moving average filter based technique. The same filtering method is used to eliminate eye blink signal along with selecting the different sub bands of the EEG wave from clean signal. A simple and robust method using db4 as mother wavelet is adopted for selection of the sub bands of EEG signal. The proposed methodology is represented in a block diagram form in Figure 1.

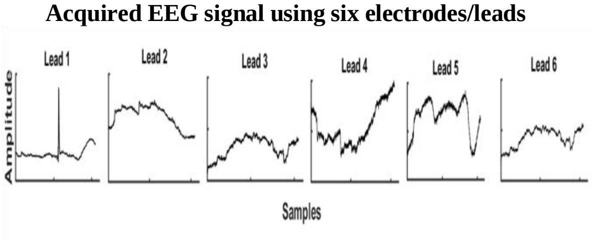
Figure 1
Block diagram of the proposed methodology for elimination of different artifacts and selection of specific sub bands of EEG signal



3.1. EEG signal

This EEG signal was recorded using non-invasive method of measurement by placing six numbers of electrodes on the human scalp following international 10-20 electrode system. All the recordings were carried out at the 'Biomedical Laboratory' at University of Calcutta, India. EEG recording was done using BIOPACK Systems, Inc. MP150 having six separate channels which can be configured individually. For the present work, the gain of the amplifier was selected to be 20000. EEG data were recorded from thirty individuals in their normal healthy physical condition. Each subject was requested to be in idle and relaxed condition keeping their eyes closed for almost ten minutes before recording. At first, they were asked to see straight towards a mark on the wall at the same level with their eye and the acquisition was started after one minute at this condition. Then they were asked to focus on same type of mark positioned at the same level but at about an angle of 30 degrees to the right and left of the first mark (central) respectively. Similarly recordings were carried out for the marks kept about 30 degrees above and below the central mark. For each case, data were recorded for an interval of five minutes. The data recorded were saved in .csv file format and .txt file format for further processing. All volunteers had filled up the form for their consent and approval for their participation in this work. The volunteers were explained about the use of the data and were assured that their personal information will be kept confidential. Before the experimental procedure, a signed informed consent form was collected from each of the participants as per the institutional and the international protocol. One such representative EEG record is shown in Figure 2.

Figure 2
Acquired EEG signal using six electrodes/leads

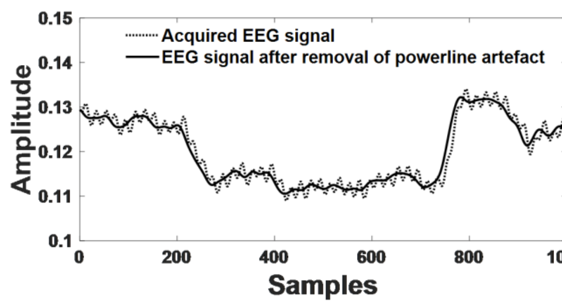


3.2. Elimination of power line artifact

A During the recording of EEG signal, there was a power line noise interference effect on the recorded signal. This noise removal was carried out before further processing. As the sampling rate of recorded EEG signal was 1 KHz and the power line frequency component was 50Hz, the size of the sliding window (N) was calculated using the Eq. (1), where fs and f represent sampling frequency and power line noise frequency respectively. The method of moving average filtering technique is efficient to eliminate artifact from biomedical signals [13]. The power line noise was removed using the 'method of twenty point moving average'. The method of twenty point moving average selects a window size of twenty samples at a time and computes the average amplitude value from these amplitudes of twenty samples. The average values thus obtained is substituted in the position of the starting point sample value of the chosen window. This process is iterated for the entire data array under consideration and every point of the array is replaced by the average amplitude values obtained during every iteration. The new array obtained after replacing all the sample values gives the clean data array which is free from power line artifact. One such power line affected acquired EEG signal and corresponding filtered signal is shown in Figure 3.

$$N = \frac{f_S}{f} = 20 \tag{1}$$

Figure 3
Representative plot of acquired EEG signal and the power line noise filtered EEG signal



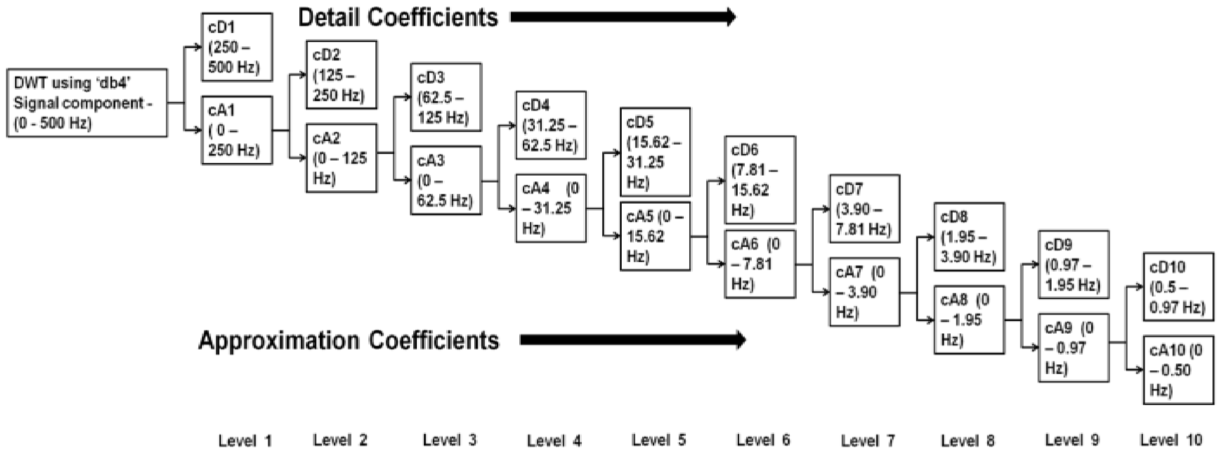
3.3. Elimination of high frequency artifact

Since the sampling rate was chosen to be 1 KHz, the highest possible signal frequency component was 500Hz. As the theoretical range of EEG signals were in between 0.5Hz to about 65Hz, as shown in Table 1, the frequency components above 62.5Hz were eliminated using the filter bank effect of DWT. Discrete Wavelet transform based technique is suitable and effective solution for denoising EEG signals [18]. DWT is carried out using 'db4' as mother wavelet for ten successive stages in order to extract the frequency components below 0.5Hz. The iterative levels of DWT along with the respective frequency ranges are shown in Figure 4.

Table 1
EEG Sub-band Frequency Components

EEG Sub bands	Theoretical Range
Delta	0.5 - 4 Hz
Theta	4 – 7 Hz
Alpha	8 – 13 Hz
Beta	13 – 30 Hz
Gamma	30 – 65 Hz

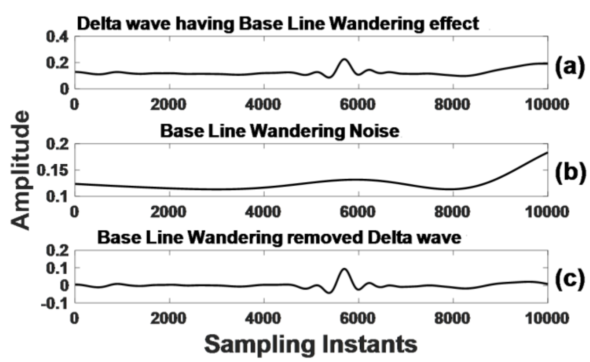
Figure 4
DWT iterative levels along with respective frequency ranges



3.4. Elimination of baseline wandering artifact

The baseline wandering noise signal frequency component was very low (< 0.5Hz) and was removed from the acquired data which is actually the approximation coefficient of the tenth stage of iterative DWT analysis. The delta wave had the frequency range closest to that of the baseline noise and hence got affected the most due to the presence of this artifact. One such plot of delta wave which contains baseline noise signal superimposed on EEG sub band, extracted baseline noise and baseline removed signal is shown in Figure 5.

Figure 5
Representative plot of (a) Delta wave having baseline noise component, (b) extracted baseline wandering noise and (c) the filtered signal



3.5. Elimination of eye blink artifact

The most prominent artifact which can be identified from the filtered signal with normal eye was eye blink artifact. The most distinguishable feature of the eye blink signal lies in its high amplitude and low frequency characteristics. Eye blink signal can be easily detected by the use of slope detection technique. One such instance of eye blink signal which can be identified from all the EEG sub bands is shown in Figure 6 where the presences of eye blink noise can be seen affecting all the bands. These instances of eye blinks were identified from entire coefficient array from delta sub band where the eye blink is the most prominent as compared to all other bands. The starting and ending instants of eye blink signals were detected using slope detection technique. One such EEG sub band signal is depicted in Figure 7 where the detected eye blink pulse is highlighted using a contrasting colour marker. In a similar way all the positions of eye blinks were detected from each band using the same instant values as the occurrence of eye blink was same for all the bands. A sliding window was chosen accordingly and it was shifted starting from the occurring instant of an eye blink to the ending instant. For each of these instants, the values of the original signal were replaced by the calculated average value of the same band signal chosen one second before and after the given instant. This method of eye blink noise removal is unique and has not been reported in the literature till date. Thus a new data array was obtained which was free from the eye blink artifacts. The filtered signal was stored in a separate array. One such comparison plot of a representative EEG sub band signal having eye blink signal and the corresponding filtered signal is shown in Figure 8. The proposed method of eye blink noise elimination is unique and not available in literature till date to the best of our knowledge. The slope detection technique used in the method yields accurate results for signal which are having low and high frequency artifacts. The method is highly accurate and is effective for even highly noise corrupted signal. One representative plot of extremely noisy corrupted EEG band and its corresponding filtered signal is shown in Figure 9. The figure depicts the effectiveness of the proposed method for low and highly noise corrupted EEG signal.

Figure 6
Representative plot of five EEG sub bands signals containing eye blink artifact

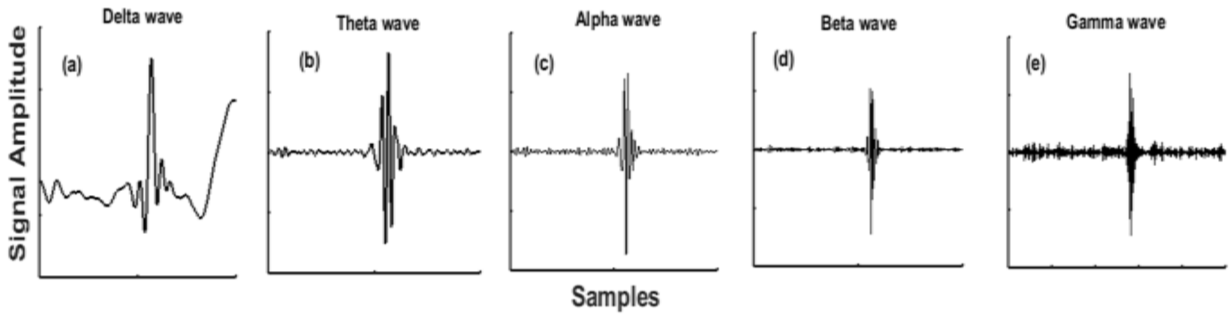


Figure 7
Representative plot of detected eye blink signal from a sub band of acquired EEG signal which is highlighted with red colour marker

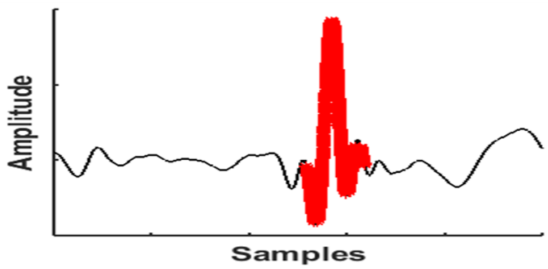


Figure 8
Comparison plot of a representative EEG sub bands with and without eye blink artifact

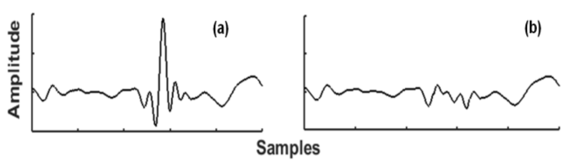
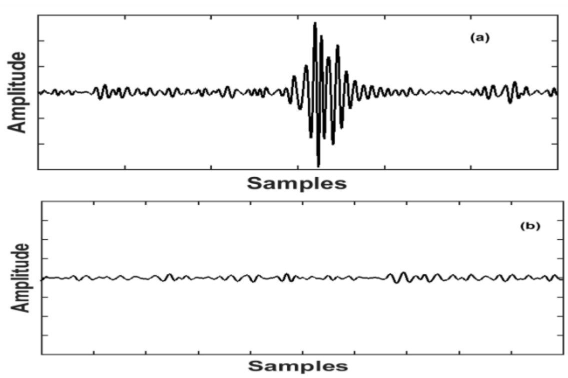


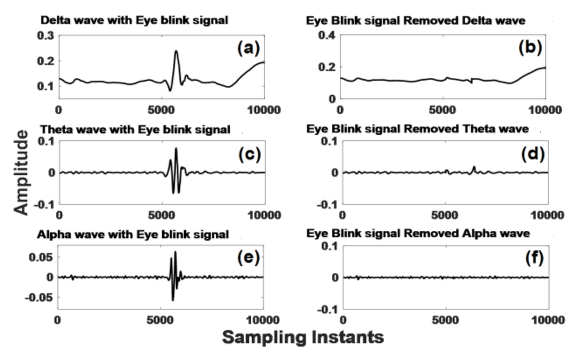
Figure 9
Representative plot of (a) extremely noisy EEG band and (b) corresponding filtered EEG band



3.6. Selection of coefficients for obtaining clean EEG

The coefficients corresponding to the sub bands of delta, theta, alpha, beta and gamma are selected from the detail and approximation coefficients and inverse DWT is performed to get back the filtered EEG signal. The selected EEG sub bands are free from all the above mentioned artifacts and the clean EEG sub bands are represented in Figure 10 alongside their counterpart having eye blink artifact. The clinical information of the EEG signal is retained even after the filtering stage which is essential for further feature extraction process.

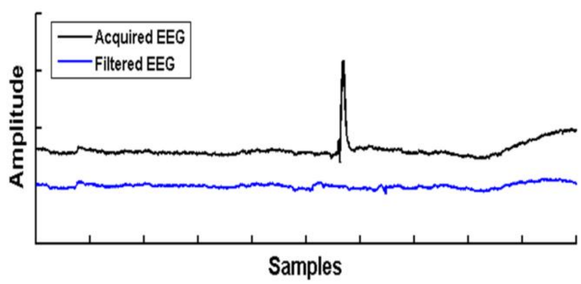
Figure 10
Representative plot of EEG sub band (a) with and (b) without eye blink artifact



4. Results

The above figures demonstrate the appropriateness and applicability of the proposed method of artifact elimination from recorded EEG signals. At each stage, the noise components were selectively eliminated and the frequency components of the EEG sub bands are kept unaltered as much as possible. The proposed algorithm had been tested on real time data recorded from thirty individuals and the result showed satisfactory performance. The clean sub bands can be used separately for studying the generation of the different waves for different excitation of the brain. Moreover, the reconstructed signal using the inverse discrete transform can be used to study the variation of spectral power and frequency variation for application in brain computer interfacing applications. The artifact free EEG sub bands were combined together in order to compare with the acquired signal and for visual satisfaction. One such representative comparison plot of acquired EEG signal having the artifacts and its corresponding filtered signal is shown in Figure 11. The figure depicts that the overall EEG signal is not distorted due to the filtering process and the clean signal contains all the clinical features of the original waveform. This property of information retention in filtered signal is essential for biomedical signal processing and analysis. Thus it is further established that the proposed method can be implemented for future real time EEG signal processing modules.

Figure 11
Comparison plot of acquired signal and clean EEG signal



The filtering performance of the proposed algorithm is evaluated in time domain by computing the Relative Root Mean Square Error (RRMSE) between the acquired and filtered EEG signals. The RRMSE measures the amplitude distortion of the filtered EEG signals following Eq. (2)

$$RRMSE = \frac{RMS(x(n)-y(n))}{RMS(x(n))} \quad (2)$$

where x(n) represents the acquired signal and y(n) represents the filtered signal. The result obtained for the proposed algorithm is compared in terms of the evaluation parameter with other similar reported literatures and is summarized in Table 2. The RRMSE value of the proposed algorithm is much lower than the other methods which justify the effectiveness of the current work.

Table 2
Comparison of RRMSE (MEAN±SD) values between acquired and filtered EEG signals

Reported Literature	Method	RRMSE Value
Cho et al. [19]	DWT	0.84 ± 0.18
Kaya et al. [20]	DWT	0.96 ± 0.03
Torkamani-Azar et al. [21]	DWT	0.76 ± 0.23
Reichert et al. [22]	DWT	0.94 ± 0.34
Shahbakhti et al. [23]	VME-DWT	0.42 ± 0.00
Proposed method	Composite filter	0.14 ± 0.03

5. Discussion

In this current work, six numbers of electrodes were used which were implanted following the international 10-20 electrode placement system. The data acquisition system had six separate channels which can be configured separately for its gain and sampling rate. For the present work, we had selected a sampling rate of 1000 samples per second for each channel while the gain was selected to be 20000. The number of electrodes could have been increased in order to get more number of channels for further accurate interpretation of EEG signal frequency components and artifact removal. The sampling rate could be set even higher than 1000 in order to get more number of data for each channel. There might be few artifacts present in the filtered signal which might had came from some slight muscle movement during recording, although care was taken so that the subject did not move. One can use this method for removal of eye blink artifact and other noises for a data length of several minutes or more. Although we have eliminated the eye blink artifact as one of the important noise component from our data, it should be kept in mind that this eye blink signal can also be used as a signature property in some application area where this signal might indicate some mental state such as hypertension, sleep disorders along with physical conditions of restlessness, palpitation, brain computer interfacing applications and many more. From the above results, it can be easily stated that the novel method or approach presented in this paper has got the potential to standalone in its field proving its existence by virtue of the ability to eliminate all possible major artifacts which might occur during the acquisition of EEG signal from an individual. Identification and elimination of eye blink peaks from the coefficients corresponding to all the channels have been executed successfully and can be visible from the comparison plots of the coefficients before and after noise elimination. The composite filter bank effect was achieved by the use of moving average and discrete wavelet transform based filtering techniques. Both the filters were adequate enough to operate simultaneously without introducing any appreciable delay. The novelty of the proposed method lies in the use of computationally simple and effective technique for all possible major artifact elimination without any loss of clinical information. The reconstructed coefficients after eye blink elimination revealed continuity and similarity in nature with the preceding and succeeding instants and hence justify the technique. The use of DWT for artifact elimination is very popular among the researchers due to its inherent filter bank effect. Effective choice of mother wavelet results in specific segregation of the different frequency bands and thereby successful cancellation of noises components. The advantage of these filters lies in the fact that the originality of the signal in terms of its diagnostic capability is unaltered in the filtering process. The method also uses less computational time as compared to other conventional higher order filters. The degree of complexity introduced due to the use of DWT for high frequency artifact and aye blink artifact is not of much concern because of the fact that their accurate identification and removal is of much more significance for the present application. A delay of few milliseconds will not cause any appreciable effect on the application of BCI, but any noise component, which might be present due to improper filtering, will cause faulty outcome and subsequent malfunctioning. Keeping this in mind, the authors have used the above mentioned filtering techniques. The computational complexity arises due to the filter bank effect of DWT during the generation of several coefficients at successive stages. Once the artifacts are removed, the selected coefficients need to be combined together and inverse transform is carried out in order to obtain the reconstructed clean EEG signal. The challenge for the present work was the data size and the electrode positions for EEG recordings. For the ease of operation, only six channels have been considered which can be a limitation for the current study. The sampling rate was selected to be 1000 in order to have adequate data for processing. For better and accurate applications of BCI, the sampling arte may be increased to double its value, but the large size of data has to be taken into account. Moreover, the size of the data increases the overall computational time.

Although the suggested approach performs satisfactorily, it is important to take into account its drawbacks and possible fixes. Firstly, the DWT's ability to accurately detect eye blinks may be hampered by the existence of additional low-frequency aberrations like electrode drift. Therefore, before executing the suggested algorithm, a high-pass filter with a cut-off frequency of 0.2 Hz should be utilized. Secondly, the suggested technique does not identify and remove additional abnormalities like eye saccades and muscle contractions; it only detects and eliminates artifacts related to blinks. However, it can be used in combination with additional filtering techniques. Thirdly, further research may be necessary to achieve more precise performance for the suggested technique for the eye blink occurrence, which was developed through experimentation. However, these recommendations for addressing the aforementioned issues are merely conjectures that need more research.

The detailed comparison of the proposed method in terms of its performance assessment with other state-of-the-art literature is summarized in Table 3. Some of the previously reported methods are not automatic in nature while few of them are not suitable to be applied in online measurement and denoising applications. Many of the reported works are not capable of eliminating all the possible artifacts present in the EEG records.

The proposed method not only eliminates the major artifacts from the records but also can be applied for online processes and thereby widens the applicability and accuracy in the domain of EEG denoising. Clearly, the comparisons given in Table 3 are reflective of the fact that the proposed algorithm shows high efficiency in terms of its performance and robustness when compared to other related literatures.

Table 3
Assessment of the proposed algorithm when compared with other state-of-the-arts literatures

Reported Literature	Method	Artifact	Automated	Application
Gao et al. [24]	CCA-ICA	Ocular , Muscular	Yes	Online
Oostenveld et al. [25]	BF	Ocular , Muscular	No	General
Molla et al. [26]	EMD	Ocular	No	General
Mahajan and Morshed[17]	ICA-WT	Ocular	Yes	General
Bono et al. [27]	EMD-WT	Ocular , Muscular	No	General
Lin et al. [28]	CCA-GMM	Ocular , Muscular	Yes	General
Gabard-Durnam et al. [29]	wICA	All	No	General
Alyasseri et al. [30]	WT	Ocular , Muscular	No	General
Shahbakhti et al. [23]	VME-DWT	Eye blink	Yes	Online
Proposed Method	Moving Average, DWT	Ocular, Power line & Baseline	Yes	Online and General

6. Conclusion

An efficient, robust and computationally simple algorithm for EEG signal denoising and selection of sub bands using composite filter is reported in this paper. The application of a single moving average filter and DWT is powerful enough for power line; baseline and eye blink artifact removal along with selection of specific sub bands of clean EEG signal. The present method is able to eliminate three major artifacts along with identifying the different eye movements in an offline process. However the same techniques can be applied for an online process with a small delay of a few seconds, which might not cause any significant delay in regular application area. The delay of a few seconds is a proof of computational simplicity of the algorithm and can be applied for real time applications in the domain of BCI. The present algorithm is tested on a variety of data collected during different external conditions for testing the robustness of the method. The algorithm is able to perform equally well for less noisy and high noisy data strips. The major challenge lies in the nature and variability of EEG signal. In spite of this, the proposed method holds for real life applications. In future, the authors intend to design a system which will use only a single electrode for better comfort to the user and simplicity in processing stages and minimize the time delay for online process. Further, wireless connectivity may be added for portability and user friendly operations. The results confirm that the proposed method is capable of making a mark of itself in this domain and can be at par with other reported literatures. Moreover, this method can be implemented in real time systems because of the negligible computational time owing to the use of a simple technique.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

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