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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 that can characterize different states of action. These signals are often contaminated with different artifacts. Dominant artifacts are baseline wandering, power lines, 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 (DWT) filtering techniques. The novelty of the present work lies in the use of a moving average and DWT filter that 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 the mother wavelet reduces the computational time and complexity. The method has been tested on real-time signals acquired from 30 individuals of varying age groups. The comparative plot of acquired and clean EEG justifies the applicability and potentiality of the method for various applications including brain–computer interface. The 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 have 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 distance 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) computational efficiency; (b) filtering of contaminated EEG signals; (b) automatic operation, requiring no human intervention; (c) noninvasive nature, preserving unaltered EEG sub bands 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 aging 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 an important bio-signal that can be recorded from the surface of the 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 that can be related to some brain-related disorders. The measurements from EEG signals can be applied to rule out or confirm various mental conditions, mental stress, seizures, brain tumors, 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 characteristic of this signal is its signature property that varies from individual to individual even in the same physical or mental state. The EEG-based analysis is gaining importance in the present world because it has the potential of an emerging technique to control several

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devices such as wheelchairs for disabled persons and also for normal healthy individuals in driving an automated vehicle and controlling robots. It has a diverse application in BCI applications and for gaming consoles. 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 that 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 signals.

2. Literature Review

Motion artifacts that create 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 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 the analysis of EEG signals acquired from the human scalp. EEG signals are contaminated by the artifacts arising from the 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 eyeball, which is beyond the control of the acquisition setup. 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 that is present in all the records. Power line artifact arises due to power line connection to the acquisition setup and is normally having a fixed frequency. The use of the median filter to eliminate power lines and baseline artifacts from the Electrocardiogram (ECG) signal has also been reported in the literature [12]. Although the median filter can be used to eliminate the power line noise from the recorded signal, the filter introduces an additional delay in the processing cycle. Moreover, the use of a higher-order Butterworth filter is available in the literature [13]. But this filter gives the best result for the 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 blinks using linear filters having the cutoff frequency chosen according to the noise signal. However, this method does not satisfactorily perform because of the fact that the EEG signal is nonstationary in nature along with the non-periodicity of the noises. The overlapping of the different waveforms of EEG with that of the eye blink signal is the major challenge with regard to its elimination. One of the normal methods to eliminate ocular artifacts is the regression-based method. However, there is a need of recording the Electrooculogram (EOG). Several time domain techniques and filtering provide substantial loss of valuable data pertaining to the condition of the brain which might lead to faulty conclusions. The use of principal component analysis (PCA), independent component analysis (ICA), wavelet denoising, and automated denoising [14] for the elimination of artifacts have been reported in the 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 preprocessing 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 electrooculogram (EOG) signal record for reference. Thus, it becomes a time-consuming and unsuitable process. Some researchers have used the Laplacian filtering technique for removing the artifacts. These filters are used to enhance the electric activities that 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 the 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 (DWT), 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 a wavelet transform-based technique [17].

Although activity related to eyeball movements can be directly measured from the EEG by placing leads near the eyes, these measurements can give the estimation of eyeball movements but are often corrupted due to the presence of EOG signals. Thus, the method of subtraction of the EOG is, therefore, not a viable solution. The 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 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 for calibration data and inverse source solutions of EOG and EEG for improving the accuracy of this method. The automatic method of EOG artifact elimination using blind component analysis and separation was also used along with the help of one additional EOG electrode. However, the use of a median filter does not give equally good results for EEG signals because of the nonstationary and feeble nature of EEG signals. In view of the above literatures, it is clear that the choice of filtering technique is very crucial for the proper elimination of major artifacts from EEG before further analysis. The above methods either introduce nonlinearity in the output or distort the signal component to a certain degree, while the other techniques involved cause a loss of few data points near the cutoff frequencies, which becomes a challenge from the viewpoint of clinical information content. This initiates the use of such a filtering technique that 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 DWT-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 the EOG signal is treated as one of the artifacts. 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 a 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 literature use higher-order Butterworth and Chebyshev filters for noise elimination, but they do introduce a loss of vital signature properties of the clinical signal. The use of the unique averaging technique for the removal of eye blink artifacts 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 three different sections, which are the 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 DWT and moving average filter-based techniques. The same filtering method is used to eliminate the eye blink signal along with selecting the different sub-bands of the EEG wave from a clean signal. A simple and robust method using db4 as the mother wavelet is adopted for the selection of the sub-bands of the EEG signal. The proposed methodology is represented in a block diagram form in Figure 1.

3.1. EEG signal

This EEG signal was recorded using a noninvasive method of measurement by placing six numbers of electrodes on the human scalp following an international 10–20 electrode system. All the recordings were carried out at the "Biomedical Laboratory" at the University of Calcutta, India. EEG recording was done using BIOPAC Systems, Inc. MP150 having six separate channels that can be configured individually. For the present work, the gain of the amplifier was selected to be 20,000. EEG data were recorded from 30 individuals in their normal healthy physical condition. Each subject was requested to be in idle and relaxed condition keeping their eyes closed for almost 10 min before recording. At first, they were asked to see straight toward a mark on the wall at the same level with their eye, and the acquisition was started after 1 min at this condition. Then they were asked to focus on the same type of mark positioned at the same level but at about an angle of 30° to the right and left of the first mark (central), respectively. Similarly, recordings were carried out for the marks kept about 30° above and below the central mark. For each case, data were recorded for an interval of 5 min. The data recorded were saved in.csv file format and.txt file format for further processing. All volunteers had filled out 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 would be kept confidential. Before the experimental procedure, a signed informed consent form was collected from each of the participants as per the institutional and international protocol. One such representative EEG record is shown in Figure 2.

3.2. Elimination of power line artifact

During the recording of the 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 the recorded EEG signal was 1 KHz and the power line frequency component was 50 Hz, the size of the sliding window (N) was calculated using Equation (1), where f_s and f represent sampling frequency and power line noise frequency, respectively. The method of moving average filtering technique is efficient to eliminate artifacts from biomedical signals [13]. The power line noise was removed using the "method of 20-point moving average." The method of 20-point moving average selects a

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

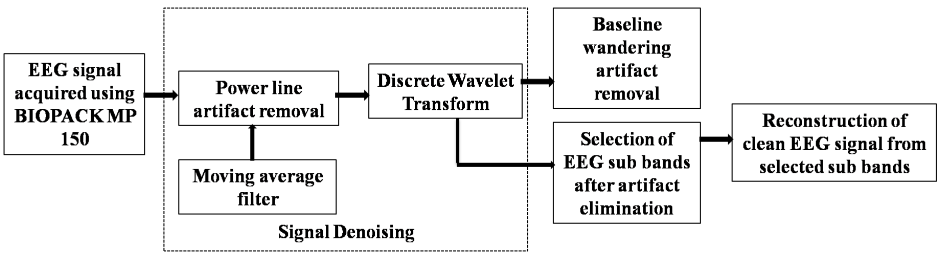
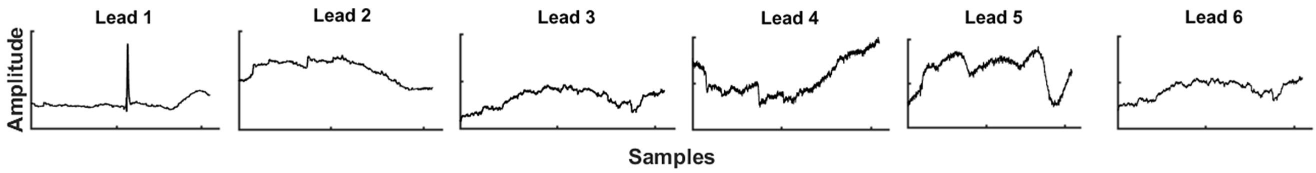


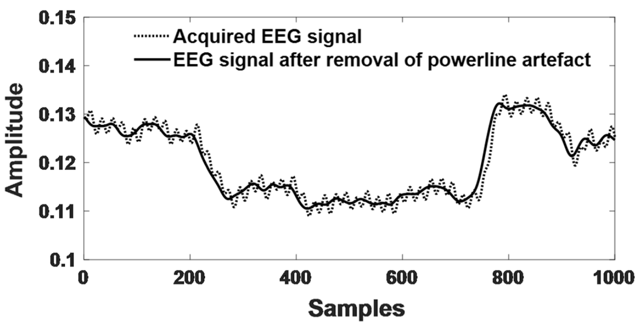
Figure 2
Acquired EEG signal using six electrodes/leads



window size of 20 samples at a time and computes the average amplitude value from these amplitudes of 20 samples. The average values thus obtained are 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 a clean data array that is free from power line artifact. One such power line affected the acquired EEG signal, and the 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 500 Hz. As the theoretical range of EEG signals were in between 0.5 Hz and about 65 Hz, as shown in Table 1, the frequency components above 62.5 Hz were eliminated using the filter bank effect of DWT. The DWT-based technique is a suitable and effective solution for denoising EEG signals [18]. DWT is carried out using "db4" as the mother wavelet for ten successive stages in order to extract the frequency components below 0.5 Hz. The iterative levels of DWT along with the respective frequency ranges are shown in Figure 4.

3.4. Elimination of baseline wandering artifact

The baseline wandering noise signal frequency component was very low (<0.5 Hz) 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 was 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.

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

3.5. Elimination of eye blink artifact

The most prominent artifact, which can be identified from the filtered signal with a normal eye, was the 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 an eye blink signal, which can be identified from all the EEG sub-bands, is shown in Figure 6, where the presence of eye blink noise can be seen affecting all the bands. These instances of eye blinks were identified from the entire coefficient array from the 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 the 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 color 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 blinks was the 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 an eye blink signal and the corresponding filtered signal is shown in Figure 8. The

Figure 4
DWT iterative levels along with respective frequency ranges

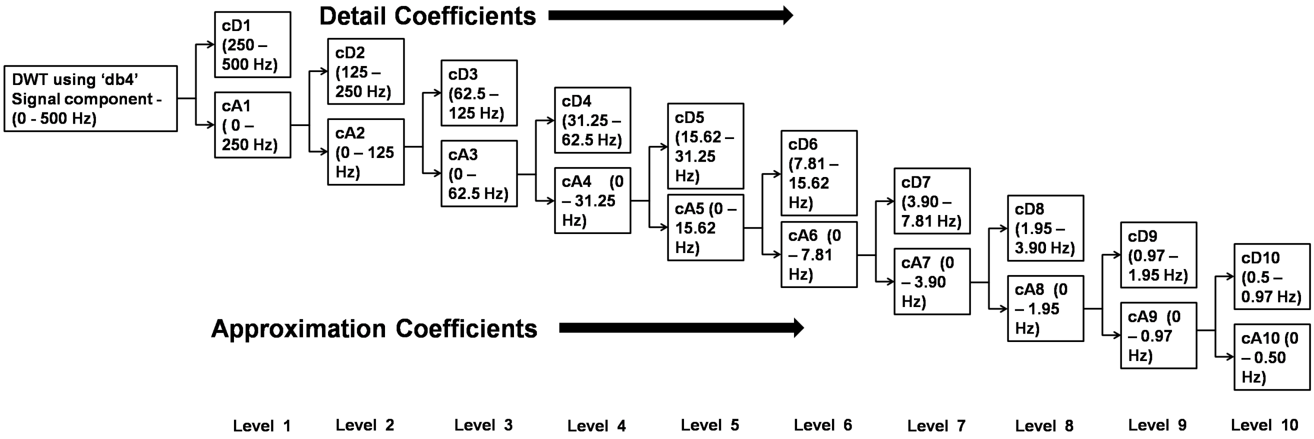
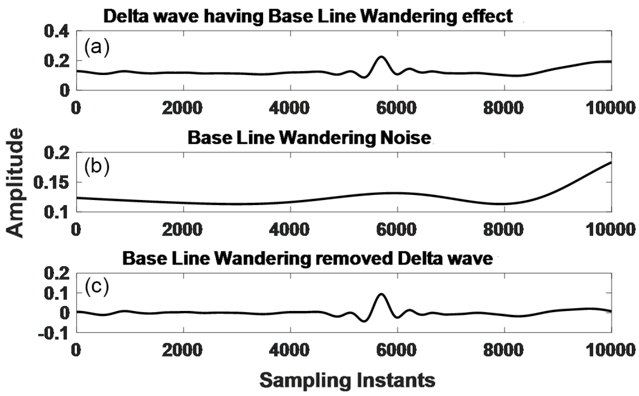


Figure 5
Representative plot of (a) delta wave having baseline noise component, (b) extracted baseline wandering noise, and (c) the filtered signal



proposed method of eye blink noise elimination is unique and not available in the literature till date to the best of our knowledge. The slope detection technique used in the method yields accurate results for signals that are having low- and high-frequency artifacts. The method is highly accurate and is effective for even highly noise-corrupted signals. 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 signals.

3.6. Selection of coefficients for obtaining clean EEG

The coefficients corresponding to the sub-bands of the 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 abovementioned artifacts, and the clean EEG sub-bands are represented in Figure 10 alongside their counterpart having an eye blink artifact. The clinical information of the EEG signal is retained even after the filtering stage, which is essential for further feature extraction processes.

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 were kept unaltered as much as possible. The proposed algorithm had been tested on real-time data recorded from 30 individuals, and the result showed satisfactory performance. The clean sub-bands can be used separately for studying the

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

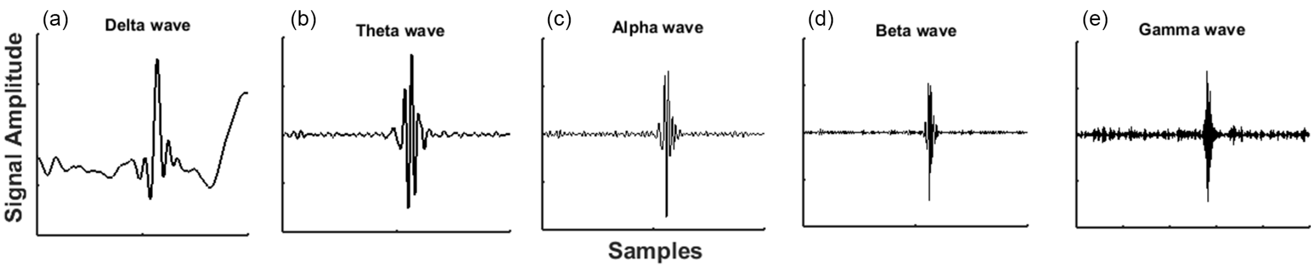
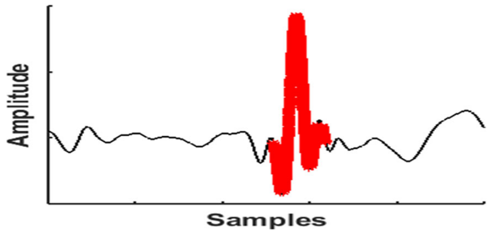


Figure 7
Representative plot of detected eye blink signal from a sub-band of acquired EEG signal, which is highlighted with red color marker



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 the 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 signals 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.

The filtering performance of the proposed algorithm is evaluated in the 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 Equation (2)

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

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 that justify the effectiveness of the current work.

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 selected a sampling rate of 1,000 samples per second for each channel, while the gain was selected to be 20,000. 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 1,000 in order to get more number of data for each channel. There might be a few artifacts present in the filtered signal, which might had come from some slight muscle movement during recording, although care was taken so that the subject did not move. One can use this method for the removal of eye blink artifacts 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 components 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 areas, where this signal might indicate some mental states such as hypertension and sleep disorders along with physical conditions like restlessness and palpitation;

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

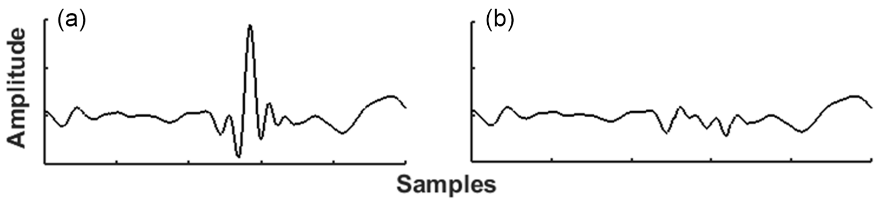


Figure 9
Representative plot of (a) extremely noisy EEG band and (b) corresponding filtered EEG band

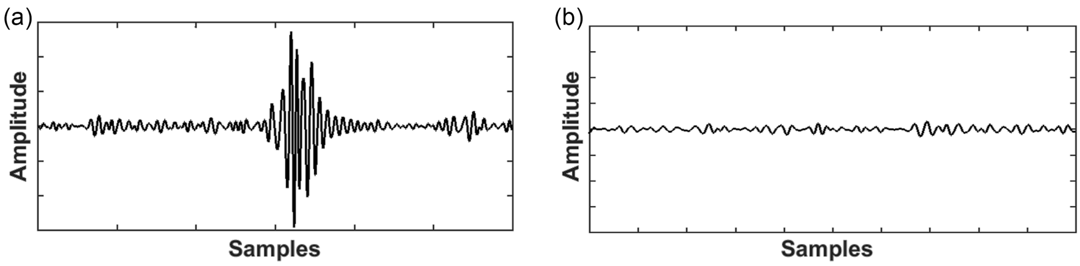


Figure 10
Representative plot of EEG sub-band (a) with and (b) without eye blink artifact

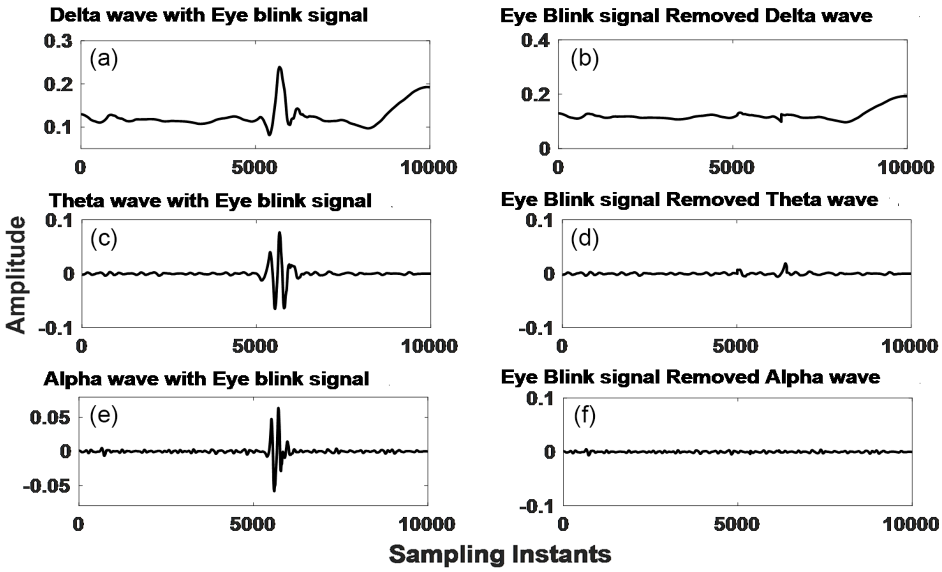


Figure 11
Comparison plot of acquired signal and clean EEG signal

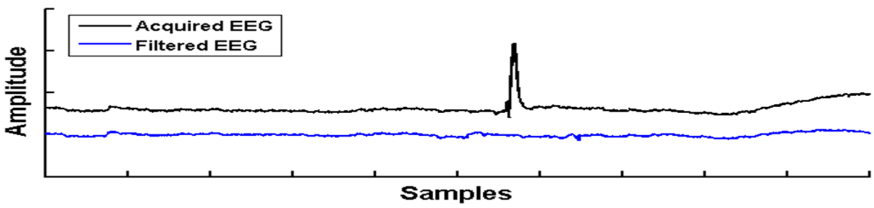


Table 2
Comparison of RRMSE (mean ± SD) values between acquired and filtered EEG signals

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

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 the potential to stand alone in its field proving its existence by virtue of the ability to eliminate all possible major artifacts that 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 DWT-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 a 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 noise 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 are of much more significance for the present application. A delay of a 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 a faulty outcome and subsequent malfunctioning. Keeping

Table 3
Assessment of the proposed algorithm when compared with other state-of-the-art 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, and baseline	Yes	Online and general

this in mind, the authors have used the abovementioned 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 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 1,000 in order to have adequate data for processing. For better and more accurate applications of BCI, the sampling rate 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. First, 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 cutoff frequency of 0.2 Hz should be utilized. Second, 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. Third, 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.

6. Conclusion

An efficient, robust, and computationally simple algorithm for EEG signal denoising and selection of sub-bands using a composite filter is reported in this paper. The application of a single moving average filter and DWT is powerful enough for power line and baseline and eye blink artifact removal along with the 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 to an online process with a small delay of a few seconds, which might not cause any significant delay in the regular application area. The delay of a few seconds is a proof of the 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 highly noisy data strips. The major challenge lies in the nature and variability of EEG signals. In spite of this, the proposed method holds for real-life applications. In the 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.

Author Contribution Statement

Avishek Paul: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Saurabh Pal** and **Madhuchhanda Mitra:** Conceptualization, Investigation, Writing – review & editing, Supervision, Project administration.

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