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EEG Eye Blink Artifacts Removal with Wavelet Denoising and Bandpass Filtering

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Abstract

Many data sources can be analyzed using Wavelet Transforms (WT), a mathematical technique frequently used for extracting information from them. Although WT was effective at Blind Source Separation (BSS), it had some limitations, such as signal loss. The problem has been addressed with the introduction of a joint algorithm that combines WT with Frequency Domain Filtering (BPF). Wavelet Denoising Technique (WDT) and Band-Pass Filtering (BPF) are employed in this research to propose an innovative algorithm for combining advanced wavelet transform methods. Combining these two techniques helps reduce eye flutter in electroencephalograms (EEGs).FP1 signals produced by eye movement are filtered out by this novel algorithm. EEG signals should be captured dependably. Combined WTs perform better than traditional WTs, according to evidence. Based on Signal-to-Noise-Ration (SNR) and Power Spectral Density (PSD) measurements, the removal process has been demonstrated to be more efficient than a standard WT.

Keywords: Analyzing of Signal, Blinking of Eye, Electroencephalogram (EEG), Processing of Bandpass Filtering (BPF), Wavelet Transformation (WT).

Introduction

EEGs are inexpensive and noninvasive methods for examining brain function[1]. Among its applications are neurological research, diagnosis of sleep disorders, and assessing the impact of antiepileptic medications[2]. An EEG brain signal exhibits[3] particular characteristics, including electrode recording, complex spatiotemporal patterns, precise time-sensitivity, limited spatial resolution, and electrode placement [4]. Artifacts are documented actions of non-cerebral origin. Artifact signals, such as eye blinking [5], can interfere with EEG signals and make the analysis process more challenging.

Recent research has focused on removing eye blinking artifacts using techniques such as independent component analysis (ICA) [6], eye tracker-based reference [7], and wavelet transform [8]. These artifact channel-reference signals are used as constraints in blind source separation algorithms to

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improve the isolation process or to check the performance of separation algorithms [9].

Borah, et al. [10], explores the use of EEG signals for controlling smart home automation systems. By integrating a TGAM EEG sensor module with a Bluetooth module, the study develops a Brain Computer Interface (BCI) system that interprets brain states and external triggers to control connected appliances. The system demonstrates a large bandwidth, easy setup, blink detection using Morphological Component Analysis (MCA), and high accuracy at a low cost. Testing shows an average response time of 17.13 seconds for switching ON and 20.66 seconds for switching OFF, with accuracies of 98.73% and 95.75% for ON and OFF states, respectively. A study of EEG-based Brain-Computer Interfaces (BCIs) examining their potential applications in a variety of fields including prosthetics, control systems, and brain-computer interfaces is reported in this article. By implementing a Convolutional Neural Network (CNN), Marcin et al. [11] attempted to remove eye blinking artifacts from EEG recordings. An augmented EEG signal approach was used to train CNN. Based on synthesized EEG signals and real EEG signals, they compared CNN performance with independent component analysis (ICA) and regression. EEG artifacts were effectively removed from the electrodes located in the central part of the head using CNN, which outperformed other methods.

Based on ML Giudice's [12] algorithm, involuntary eye blinks can be detected and distinguished from voluntary ones. In order to help individuals with motor disabilities, we are developing an EEG-based Brain-Computer Interface (BCI) that can be controlled with eye movements. With the help of frontopolar EEG signals obtained from healthy individuals, the proposed algorithm was trained and validated using a one-layered Convolutional Neural Network (CNN). In identifying voluntary and involuntary blinks with 97.92% accuracy, the system achieved 97.92% accuracy.

According to Mayeli A. et al. [13], a fully automated pipeline is offered by the open-access toolkit Showup that reduces artifacts from EEG data collected simultaneously with fMRI. By utilizing both standard template subtraction and independent component analysis, the pipeline suppresses MRI-related artifacts as well as physiological artifacts. The results show that the automated correction using APPEAR is comparable to manual correction, as demonstrated by frequency analysis, continuous wavelet transformation, and analysis of event-related potentials (ERPs). The significance of APPEAR lies in its ability to speed up EEG analysis, enhance replication, and process large EEG-fMRI datasets with manageable researcher time and effort, thus addressing the challenges associated with EEG artifacts in the context of simultaneous EEG-fMRI recordings.

Mathe M, et al. [14], proposed intelligent model based on deep learning, specifically the improved One-Dimensional Convolutional Neural Networks (1D-CNN). The model utilizes a hybrid algorithm called Spider Monkey-based Electric Fish Optimization (SM-EFO) to optimize the parameters of the 1D-CNN. Experimental results on a benchmark dataset demonstrate the superior performance of the proposed model in terms of artifact removal, achieving cleaner waveforms compared to conventional approaches.

Krishnaveni V, et al. [15], proposed a method for automatically identifying slow varying OA zones and applying adaptive thresholding only to these zones, preserving the non-OA zones and the shape of the EEG signal. This approach allows for the removal of artifacts without compromising the important low frequency components and waveform of the EEG signal in non-artifact zones, which is crucial for clinical diagnosis. Table 1 summarize the related works.

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Baghdad Science Journal

Table 1. Related works summary on artifact removal methods.

Authors, Ref.	Method	Technical Details	Shortcomings
Borah, et al.[10]	TGAM EEG sensor + Bluetooth BCI system	Large bandwidth, blink detection using MCA	Response time for switching ON/OFF
Marcin, et al.[11]	Convolutional Neural Network (CNN)	Trained using augmented EEG signals	Limited comparison to other methods
Giudice ML, et al.[12]	One-Dimensional CNN architecture	Detects voluntary vs. involuntary eye blinks	Limited focus on eye blinks
Mayeli A, et al.[13]	APPEAR toolbox for EEG-fMRI artifact reduction	Average template subtraction + ICA	Relying on EEG-fMRI data
Mathe M, et al.[14]	Improved 1D-CNN with Spider Monkey-based EFO	Hybrid algorithm optimization	Limited benchmark dataset
Krishnaveni V, et al.[15]	Automatic identification of slow varying OA zones	Adaptive thresholding for artifact removal	Limited to slow varying OA zones
Proposed system	Evolutionary Wavelet Transform (EWT) + BPF	Eliminates eye blink artifacts in FP1 channel EEG	Efficient EEG artifact removal using hybrid approach.

Many works address issues related to network performance, security, privacy, authentication, and communication efficiency in wireless systems, such as ad hoc wireless networks[16], mobile ad hoc networks[17], 5G-enabled vehicular networks[18, 19, 20], and fog computing-based solutions[21]. BiCM improves wireless sensor network coverage through instance redeployment in two stages: DES relocation and depuration. It outperforms FOA in coverage, computation time, and standard deviation after parameter optimization[22]. LCX-MAC enhances time-critical IoT healthcare applications, addressing X-MAC's energy waste and delays. Analytical results show LCX-MAC outperforms X-MAC and X-MAC/BEB in throughput, delay, and energy efficiency[23].

Efforts continue to tackle wireless sensor communication challenges. NRSM optimizes node positions, surpassing FOA, JOA, and BFA in coverage, computation time, standard deviation, and energy efficiency, enhancing network performance[24]. While it discusses healthcare monitoring, it does not directly relate to eliminating eye blink artifacts in EEG signals.

The study's primary contributions lie in the development and evaluation of an effective algorithm for eliminating eye blink artifacts in EEG data, providing valuable insights into artifact removal techniques, and showcasing the importance of artifact-free EEG signals for accurate brain activity measurement.

The paper proposes a method for eliminating eye blink artifacts in EEG signals captured from frontopolar FP1 channels. This system uses a combination of wavelet denoising and bandpass filtering techniques to effectively remove the artifacts while maintaining the essential EEG signals. The implementation of the system is also described in detail.

Both simulated and real EEG data were used in the study to evaluate the proposed system. This system is demonstrated to be effective in removing eye blink artifacts while maintaining EEG signals. A summary of the contributions of the paper and its implications for EEG signal analysis is presented at the end of the paper. Furthermore, the paper discusses the system's limitations and suggests future research avenues. EEG signals from the frontopolar FP1 channel show eye-blinking artifacts from the proposed system.

Materials and Methods

Traditional Eye Blink Artifact Reference Signal Algorithms

In the realm of sign processing and neurophysiology, several methods have been developed to detect and mitigate or analyze eye blink artifacts across various applications[25]. Some conventional methods commonly used for eye blink artifact removal are:

1. Moving Average: This straightforward technique calculates the average value of the signal over a moving window. It serves as a baseline signal for estimating the standard or non-artifact portion of the signal. Subtracting the moving average from the original signal helps attenuate eye blink artifacts[26].

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2. Template Matching: Template matching algorithms employ a predefined eye blink template as a reference signal. The template, created by averaging multiple eye blink signals to capture typical characteristics, is then correlated with the input signal to identify similar patterns associated with eye blink artifacts[27].
3. Adaptive Filtering: Adaptive filtering techniques employ adaptive algorithms such as Least Mean Squares (LMS) or Recursive Least Squares (RLS) to continuously estimate eye blink artifacts. These algorithms adjust filter coefficients based on the input signal and the error between the filtered signal and the original signal, aiming to minimize artifacts[28].
4. Principal Component Analysis (PCA): PCA, a statistical method for dimensionality reduction, can be utilized for eye blink artifact removal by decomposing the signal into principal components. Selecting a subset of components that capture the eye blink artifacts yields an estimated reference signal.
5. Independent Component Analysis (ICA): ICA is another statistical technique that separates a multivariate signal into statistically independent components. For eye blink artifacts, ICA can identify and isolate the component associated with eye blinks, providing a reference signal for artifact removal.

These methods represent traditional approaches, while the field of signal processing continues to evolve. Recent advancements, including deep learning techniques and adaptive signal processing algorithms, have also been employed to address eye blink artifacts with promising outcomes.

Technical Artifacts

In this critique, we introduce a robust approach for computing a prominent eye blinking cue reference signal, which incorporates wavelet de-noising and bandpass sifting (BPF) techniques. The evaluation of strategies for segregating impaired source signals typically involves simulated data, with the interference signal ratio (ISR) serving as a performance metric[29]. Electroencephalography (EEG) systems are designed to measure a biological signal reflecting the brain's electrical activity, achieved by placing electrodes on the scalp. However, EEG signals are often characterized by irregular, low-amplitude fluctuations that can be influenced by artifacts (see Fig. 1.a), defined as non-cerebral-origin behaviors. EEG, a non-invasive technique, records the brain's electrical activity[30]. Nevertheless, the recorded EEG signal frequently suffers from various types of artifacts, such as power line noise, muscle activity, eye blinks, and electrocardiography (ECG) artifacts. These artifacts can obscure the underlying EEG signals and compromise the accuracy of analysis. Hence, it is imperative to separate these artifacts from the EEG signal before conducting any analysis.

Technical artifacts are unwanted signals that can contaminate EEG data and affect its accuracy. One such artifact is ***power line noise interference PLN***, which is caused by extremely high signals generated from A/C power sources during the recording phase. These signals have lower frequency and harmonics and can be removed using a notch filter. However, the notch filter also removes EEG data that is useful information and is approximately 50/60 Hz. Fig. 1.b shows the EEG signal with the noise of the power line [31].

Another common artifact is ***eye blink or eye movement***. These signals are produced by blinking or movement of the human eye, which changes the dipole electrically created by the positive cornea (red) and negative retina (black) to create eye artifacts. The duration of an eye blink artifact is less than 4 Hz, and it has a low spread and a spike shape as shown in Fig. 1.c. On the other hand, eye movement has a high spread, and both eyeblink and eye movements have a square shape as shown in Fig. 1.d [32].

Electrocardiography (ECG) artifacts are caused by heartbeat activity when the electrode is placed on or near a blood vessel. Cardiac activity has a high electrical energy effect on EEG signals. Fig. 1.e displays ECG events that occur as continuous spikes in the EEG recording process [33].

(a) The correct EEG signals.

(b) EEG infected with the PLN.

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(c) EEG infected with the eye blinks.

(d) EEG infected with the eye movement.

Figure 1. Typical artifacts of the EEG[29].

Bandpass filtering and wavelet denoising are complementary techniques used in EEG artifact removal. Bandpass filtering helps isolate the frequency range of interest, including the eye blink artifacts, while wavelet denoising further enhances artifact removal by effectively targeting and removing unwanted components within that range. Together, these techniques improve the quality of EEG data for analysis and interpretation.

Artifacts Removal Techniques

All through the recording system, the information was sullied with different sorts of artifacts. The EEG signals of these artifacts ought to be cleaned for study. There are different techniques utilized for this reason. To eliminate these artifacts from the recorded EEG information, different techniques are utilized. A few normal methods for curious expulsion incorporate separating, which includes applying various sorts of channels to the information, for example, score channels or bandpass channels, to eliminate undesirable signals. Another procedure is the utilization of autonomous part investigation (ICA), which isolates the information into free parts and recognizes those that contain antique signals. Wavelet denoising is likewise a well-known technique for eliminating clamor from the sign while safeguarding the basic EEG data.

Generally, the expulsion of artifacts is fundamental for precise EEG signal investigation, and analysts utilize different procedures to accomplish this objective. Every strategy enjoys its benefits and restrictions, and the decision of the method relies upon the kind and seriousness of the antiquity of the exploration question being tended to, and the accessible assets.

Manual Technique

Identifying evident artifacts like eye blinks, eye movements or muscle activity is straightforward with a visual inspection of recorded EEG data. A limited sample size makes this method common in clinical settings and research studies. Nevertheless, it is labor-intensive, subjective, and dependent on the analyst's expertise to be effective. Data fragments corrupted by identified artifacts are discarded by eliminating epochs containing those artifacts. When applied to scant datasets, it risks losing essential data, even though it is a simple method of removing artifacts from EEG signals.

A Bandpass Filtering Technique

Filtering is another common method for removing artifacts. By using a high-pass filter, low-frequency noise can be eliminated, while high-frequency noise can be eliminated by using a low-pass filter. Alternatively, a band-pass filter targets high-frequency as well as low-frequency noise. The importance of carefully choosing filter parameters is highlighted by the possibility that filtering may inadvertently remove some important EEG signals.

Band-pass filters are commonly used to separate artifacts from EEG signals. An attenuator is a device that attenuates frequencies outside of a specified frequency range while allowing signals within a preferred range to be transmitted. Band-pass filters are used in EEG analysis in order to eliminate undesirable frequencies, such as power line noise and cardiac activity, while preserving the desired signals. The bandwidth (BW) of the filter is described as [34, 35]:

$$BW = FH - FL \quad \ldots\ldots\ldots\ldots \quad 1$$

Practically speaking, the middle recurrence and transmission capacity of the band-pass channel are picked in view of the recurrence scope of the EEG signs of interest. For instance, a run-of-the-mill EEG signal has a recurrence scope of 0.5-70 Hz, with the alpha cadence (8-12 Hz) and beta mood (13-30 Hz) being specifically compelling in many examinations. In this manner, a band-pass channel with a passband of 0.5-70 Hz, or a smaller passband revolved around the alpha. In any case, it is essential to take note of that utilizing a band-pass channel may likewise eliminate some EEG flags that contain significant data. Consequently, the cautious thought of channel boundaries is vital because of multiple factors. First and foremost, the exploration question being tended

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to decides the particular attributes of the EEG signs of interest. For instance, unique recurrence groups might be of specific significance relying upon the idea of the mind movement being scrutinized. By choosing fitting channel boundaries, specialists can successfully segregate and break down the ideal EEG signals while constricting undesirable commotion and artifacts. Besides, the accessible assets, like the computational power and sign handling capacities, can impact the decision of channel boundaries. Depending on the setting, certain separating methods might require more computational resources or specialized programming. Professionals can choose channel constraints based on the available resources to achieve the best filtering performance while taking practical limitations into account. Utilizing accessible devices and technologies maximizes the accuracy and reliability of EEG signal analysis.

Wavelet Noise Removal Technique

There has been a growing understanding that wavelet sound decreases can be used to remove clamor from signals since the 1990s. Using this technique, the sign is disintegrated into various scales, enabling it to be successfully disposed of. Since Donoho created thresholding in wavelet-based signal examination in 1993, it has essentially advanced wavelet-based signal examination[36]. By using wavelet coefficients as an edge, the clamor part is eliminated, eliminating the need to make assumptions about signal presence. For de-noising signals, the Wavelet De-Noising Technique has a few benefits. A relationship analysis determines the ideal result signal as a first step. With wavelet coefficients packed in two parts, the clamor is evacuated with powerful efficiency. Using the opposite Wavelet Transform, the technique reduces low commotion amplitudes while recovering signals with little data loss.

Wavelet De-Noising Methodology consists of a few components [37]:

- Applying the Wavelet Transform (WT) to the noisy signal, followed by the
- Selection of the limitation and threshold method for each step.
- Inverse Wavelet Transform (IWT) is applied to the wavelet coefficients to reconstruct the de-noised signal.

Among the many applications of the Wavelet Denoising Strategy are image processing, audio signal processing, and biomedical signal processing. The efficiency and effectiveness of this tool make it a valuable asset in many different fields.

Artefact Reference Techniques

EEG signal handling includes artifact reference procedures, which identify and eliminate artifacts that can alter the EEG signal, enabling accurate and detailed analysis. Procedures are decided based on unambiguous review necessities, such as the type of artifacts to be identified and the idea of the signals gathered. EEG analysis can discern the overall morphologies from the EEG data and contaminating blink-eye artifacts. Several techniques have been developed to extract artifact reference signals, each with its own advantages and disadvantages. The popular methods for extracting the artifact reference signal are discussed in this section [8].

Channel-Reference

Channel reference is commonly used to test the efficiency of eye blink artefact extracting algorithms by comparing the extracted eye blink artefact to the V_{EOG} channel. EOG signals are corrupted by another signal generated by the brain or by other external sources [38]. The EOG electrodes (v_{EOG} and n_{EOG}) are used as reference signals for EOG artifacts, positioned above and side of the left eye and the socket is used to assess the face movement (artifacts) as shown in Fig. 2. The electrodes are directly placed on the skin to collect the brain signals. It combines the signals in [38]:

$$X(t) = [X1(t), X2(t), ..., Xm(t)]T \quad \ldots\ldots\ldots\ldots \quad 2$$

Where the EEG signal is registered, "T" is the transmission and "m" is the channel numbers. The rows of the input matrix are EEG signals, and the columns represent the difference in the signals at various times. It is processed to remove low-frequency or high-frequency noise and other potential artifacts before the EEG signal is displayed or stored. Therefore, the critical points in its processing need to be treated carefully, so that artifacts that contaminate signals may lead to false results and assumptions are reduced. Simple signals recorded by the electrode, complex-time signals, extremely good time control, low spatial resolution, and quantity electrodes are the basic features of EEG-brain signals. In contrast to ECoG signals, EEG presents however extremely low-quality signals. It immerses almost all the EEG signals and artifact signals which corrupt the EEG data interfere. In the case of eye blinking artifacts, the EEG channel filter is usually known to be an eye blinking artefact and can be used directly as a

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reference signal on the premise which the variance is negligible in the other channels follows [39]:

ri (t) = f (qj (t))   i = 1, 2 , …., k; j = 1, 2 ,….l ………… 3

Where:

i: representing the number of reference signals utilized

f: indicating the filtering method applied

q: representing the registered signal

j: indicating the number of channels

l: representing the overall number of registered channels.

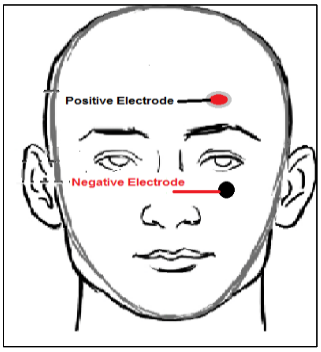

Figure 1. Electrode's position.

Template Train-Reference
In this method, a filter which is mostly considered as an artefact is applied to the channel, then converted into the tarin of templates to use it as a reference, and the shape of information is conserved. It is difficult to render a single template for an eye-blinking artefact; hence, a sample train is used as a reference. The variance in the form of the example can be modified roughly where the reference artefact is centered only on the target signal and the estimated time. Eq. 4 regulate the train-reference model system as follows [40]:

$$\left.\begin{array}{c} r_i(t+v)=f\left(q_j(t+v)\right)_{v=[-a,-a+1,\ldots,b]} \\ t\leftarrow t+b \end{array}\right\} \quad if\ \ f\left(q_j(t)\right)\geq\pm\gamma \qquad \ldots\ldots\ldots\ldots 4$$

$$r_i(t)=0 \qquad\qquad otherwise$$

Where,

i = 1, 2, ….k,
j = 1, 2, ….l,
γ – the selected threshold value,
a and b – the number of the chosen samples,
v – the set indicates the total number of assigned samples, and
t – the time of the reference signal

Principle Component-Reference
Artefact signals have a higher impedance than EEG signals and their frequency varies widely across channels. One of the key features that distinguish artefact signals is their orthogonality with EEG signals [41]. Principal Component Analysis (PCA) is a statistical technique that can be used to identify orthogonal components. However, Independent Component Analysis (ICA) is more effective than PCA in separating artefact signals from EEG spike records [42, 43]. Nevertheless, if the separation is based solely on differences in independent components, the resulting data may still reflect the overall characteristics of the artefacts. For example, in EEG recordings contaminated by eye blinks, the EEG signals are expected to project onto two major components (the strongest eigenvalues), with the resulting signals representing the basic characteristics of the eye blink artefacts. This process is represented by:

$$\mathrm{pc}(t)=\mathrm{x}^T\mathrm{E}(\mathrm{t}) \quad \text{with} \quad \mathrm{pc}(t)=\begin{bmatrix} pc_1(t) \\ pc_2(t) \\ \vdots \\ pc_n(t) \end{bmatrix} \ldots\ldots\ldots 5$$

ri (t) = pci (t)   i = 1, 2, ….., k ……   6

Where,

E – is the eigenvectors array of x^T covariance's,
pc – is the projection matrix, and
i – are the several evaluated principal components.

Proposed System

A novel algorithm is proposed to extract clean eye blink artifact reference signal from related electrodes based on a combination of filtering process and wavelet denoising technique. The proposed algorithm takes the artifact distribution on the brain's scalp into account. Fig. 3 shows the block diagram of the eye blink artifact reference signal extraction algorithm.

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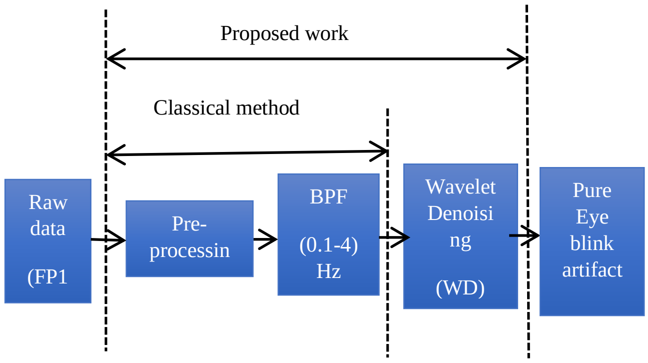

Figure 3. Block diagram of the Enhanced Channel- Reference algorithm.

The effect of ocular artifacts will be dominant in the Frontal and Frontopolar channels particularly in FP1 and FP2. The eyes are blinking together and have the same effect on frontal channels FP1 and FP2; therefore, only the FP1 channel, will be taken as an input to the proposed algorithm.

The study presents a new method called the Evolutionary Wavelet Transform (EWT) for dealing with Eyeblink artifacts in EEG signals. Eyeblink artifacts are known to produce high-amplitude impulses that can interfere with all electrodes, particularly those in the front and front polar channels such as FP1, FP2, F7, and F8. The traditional channel-reference approach to calculate blinking artifacts from the human eye involves modifying the channel reference based on the morphologies and timing of comparing the potentially contaminated electrodes. However, this approach does not effectively remove the eye blink artifact signals from the associated electrodes, leaving conventional neural signals still contaminated. The proposed EWT method uses a hybridization of bandpass filtering and wavelet de-noising techniques to remove eye blink artifacts from the EEG signals. The pre-processing procedure ensures that the input signal has zero mean and unit variance. The band-pass filter (BPF) uses the Windowed-Sinc FIR filter to reduce eye blink artifacts to the small frequency range of less than 4 Hz, with a frequency selection of 0.1-4 Hz and a length of 1024 kernel filter determined as M. The EWT method uses only the FP1 channel as a reference to simultaneously remove eye blink artifacts from both the FP1 and FP2 frontal channels as follows:

$$M \approx \frac{4}{\mathrm{BW}} \quad \ldots\ldots\ldots\ldots \quad 7$$

Where, the length of the frequency is BW. The filter kernels of the low-pass filter are determined as follows:

$$\mathrm{h[i]} = \mathrm{K}\frac{\sin(2\pi f_c(i-M/2))}{i-M/2}\left[0.42 - 0.5\cos\left(\frac{2\pi i}{M}\right) + 0.08\cos\left(\frac{4\pi i}{M}\right)\right] \ldots\ldots\ldots\ldots \quad 8$$

A band-pass filter with a cutoff frequency involves a number of parameters to determine the tap coefficient. This includes the filter's impulse response h[i], its convolution k, his length M, his cutoff frequency f_c, and his index i. Low-pass filter segments are computed at both cutoff frequencies (f_{c1}=0.1 Hz and f_{c2}=4 Hz) to obtain the tap coefficient.

1. Let M =1025, S_{rate}= 256, f_1= f_{c1}/S_{rate}, and f_2= f_{c2}/S_{rate}
2. Compute the low-pass filter kernel at f_1
3. Compute the low-pass filter kernel at f_2
4. Stabilize the two filter kernels.
5. Shift the low-pass filter kernel to the high-pass filter by spectrum transposition.
6. Incorporate the low-pass and high filter kernel to achieve the band-reject filter kernel.
7. Use spectral inversion to convert the band-reject filter kernel to the band-pass filter.

To improve the filtering process efficiency when converting input signals to filter kernels using the MATLAB "conv" function, the wavelet method can be used to eliminate residual neural impulses from the filtered signal. The filtered signal is highly active in the brain (e.g., Delta rhythm). Following wavelet de-noising (WD), the filtered signal distinguished by a low spectral traditional brain signal $n(t)$ and high-frequency artefact ą(t):

$$\mathrm{FP}_{1f}(t) = ą(t) + \mathrm{n}(t) \quad \ldots\ldots\ldots\ldots \quad 9$$

Where, FP_{1f} is the filtered front channel signal (i.e., the signal of BPF), the artefact ą(t) is located in a time or frequency domain, and $n(t)$ is the spectrum of broadband. Therefore, the wavelet transform method is appropriate for the optimum resolution of frequency, and time domain, with no stationary signal. The model of Eq. 9 be nearly additive, as band-pass and Band-Reject-filters are primarily low-pass and high-pass filter combinations. A filter band-pass makes only frequencies above and below a certain amount, so there're several frequencies. The reverse is a band-reject filter that stops a frequency

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band. Often band-reject filters are called notch filters since a certain part of a signal is detected.

Wavelet de-noising (WD) utilized to suppress the neural structure selectivity n (t) losing no artefact's portion a(t), as follows [43]:

1. Calculate the wavelet coefficients $a_{j,k}$ by discreet wavelet transformation (DWT) of the FP1 signal.
2. Calculate the soft thresholds for wavelet coefficients:

$$\hat{a}_{j,k} = \begin{cases} \mathrm{sgn}(a_{j,k})(|a_{j,k}| - T) & \text{if } |a_{j,k}| \geq T, \\ 0 & \text{if } |a_{j,k}| < T \end{cases} \quad \ldots\ldots 10$$

3. Calculate the inverse distinct wavelet transform $\tilde{a}(t)$ of the soft coefficient $\hat{a}_{j,k}$.

Where, $a(t)$ means an artefact signal a(t) without a neural signal $n(t)$. Discrete wavelet D6 was used with the level 7 separation in the suggested algorithm. The threshold for de-noises shall be determined by the following:

$$T = \sqrt{2\log(d)} \ldots\ldots\ldots\ldots \quad 11$$

Where, d is the sample number to be handled.

Results and Discussion

Real EEG data are contaminated by power line noise interference and EOG artifact (eye blink) measured by a computerized EEG device in Middle Euphrates Center for Neurological Sciences-Kufa-Iraq. The computerized EEG is a computer with a PCI card of a data acquisition unit that acquires the signals from the scalp through macro electrodes as shown in Fig. 4. One healthy subject, male, 24 years old has participated in this study. EEG signals were measured using 19 electrodes used to measure the brain signals placed on the scalp according to 10-20 system and referenced against the forehead. According to the specification of computerized EEG device the recorded signals were digitized at 256 Hz, trail length is 10 second ($10 \text{ second} \times 256 \text{ Hz} = 2560$ sampls), during which the subject was allowed to perform eye blink artifacts.

Figure 4. Computerized EEG system.

The control measures of the SNR are made up of two types: external noise reduction and internal noise separation from the signal of interest. It is best to avoid the first to deal with external noise. It is better to use high-quality instruments and electrodes to eliminate noise from the device, such as cable networks, phones, computers, machine monitoring. (e.g., most dry electrons are not functional as they are very sensitive to external noises) and to remove any electromagnetic noise sources. Compared to removing noise produced by the subject itself, this is relatively straightforward. It is not usual to ask the participant to sit still, but all blinking or facial muscle movements are practically impossible to avoid.

This issue is also solved by an intelligent experimental protocol, which can help keep participants focused and interested in the task to reduce the internal cortical noise, it can achieve frequent interruptions to constantly blink between experimental tasks. Well-trained EEG technicians will also help to make the participant happy and create a relaxed business environment for the collection of data.

After recording data, they often use advanced statistic algorithms in what they call post-processing to recognize and eliminate subject-related noise from a raw EEG signal, such as gestures, eye blinks, and muscle tensions. For instance, machine learning algorithms may recognize patterns of external or internal noise-related signals and distinguish them from the brain signals of interest. This role is mostly performed via a family of statistical techniques known as the blind signals separation (BSS) algorithms, which are widely implemented directly in commercial and open-source EEG analytical

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Baghdad Science Journal

applications. Sometimes, followed by manual cleaning, an EEG specialist visually checks the signal and manages the objects and distracting parts.

Fig. 5 shows the real FP1 data taken from the computerized EEG device with a sampling rate of 256 Hz. This signal represents the input raw data for the proposed algorithm. The units are typically expressed in microvolts (μV) per sample. Each data point in the EEG recording represents the electrical voltage measured at a specific moment in time, and it is usually reported in microvolts.

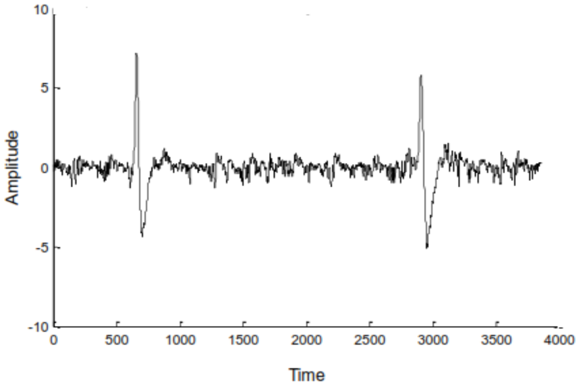
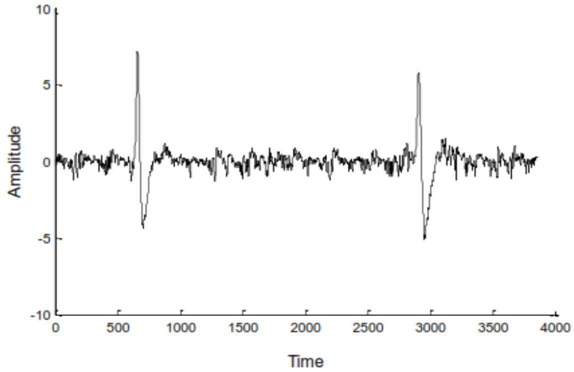
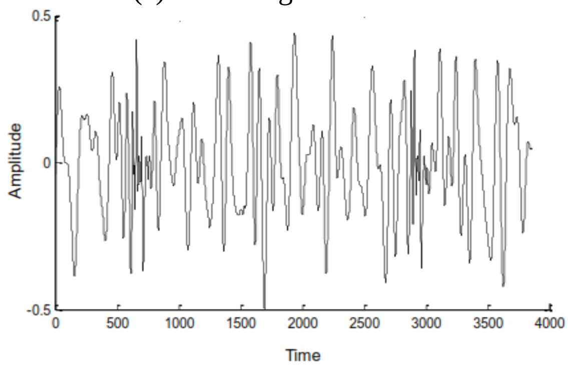


Figure 5. Un-processed FP1 data.

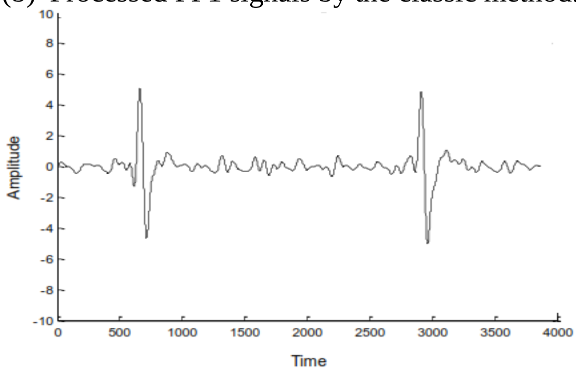
Fig. 6 shows the extraction of the signal (FP1) to unnatural, and neuronal components depending on the suggested approach. The input signal (FP1) attempted pre-processing to whiten and center the signal, as seen in Fig. 6.a, so the (BPF, 0.1-4 Hz) process the signal as stated in the suggested method writing material Fig. 6.b. According to the traditional system (channel-reference system), the filtered signal did not involve any neural activity and could be described as an eye-blinking artefact. Nonetheless, it is not just a signal of reference because it has a lot of cortical activity, Fig. 6.c. The main benefit of the proposed approach (i.e., brain activity will be omitted from the wavelet de-noising WD artefact reference signal Fig. 6.d. Visual examination of the eye blinking artefact signals shows that the suggested technique is better than the traditional method as seen in the zooming signal, Fig. 7.a, as some of the neural activity is observed in the classical method Fig 7.b. Fig. 7.b also uses band-pass filters (BPF) to resolve the defects in the wavelet, since it bases the proposed approach on the hybridization between the Band-pass Filters (BPF) process and the Wavelet Transform (WT) process to enhance its output precision.



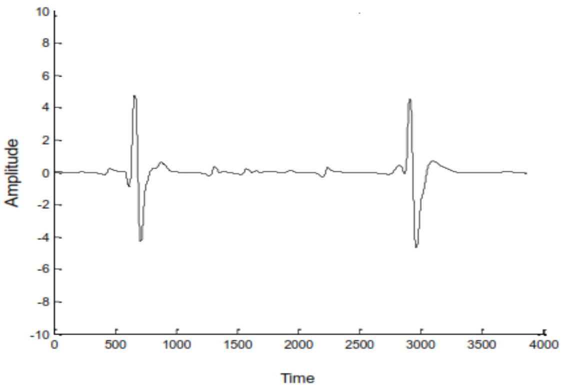
(a) Initial signal for FP1.



(b) Processed FP1 signals by the classic method.



(c) The underlying signal of the neural source is released to the processed FP1 signal.



The underlying signal of the neural source is released to the processed FP1 signal.

Figure 6. Decomposition of FP1 channel.

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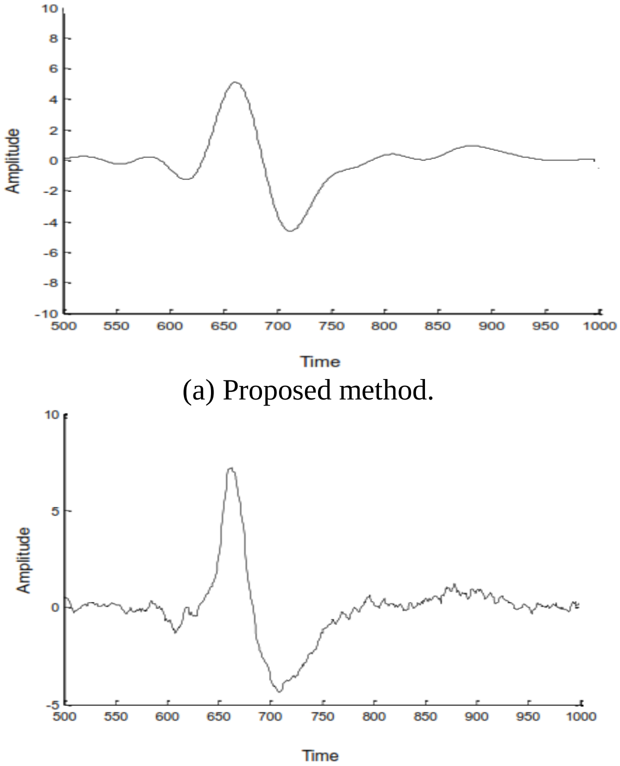

(a) Proposed method.

(b) Classical method.

Figure 7. Zoomed signals (500-1000 second).

The Kalman filter is for removing a heavy artifact form of artifact [44]. It has been effective in identifying a second window containing various kinds of objects such as muscles and motion. The filtering process, which calculates the EOG signal filtering method by a single reference signal, is used in this analysis. The application is seen and taken as two separate reference inputs based on the distinction between vertical and horizontal EOG channels. Wavelet Transformation is one of the most commonly used approaches to analyze non-stationary signals such as EEG. Table 2 shows the difference between the proposed system and previous works of removing artifacts.

Table 2. Comparison between methods of removing artifacts

Methods	Features	Limitations
Manual	Simple, less costly and no reference channels.	Loss important EEG data and impossible to control on the eye blinks for long time
Filtering	Real time; adaptable, flexible and does not require calibration trials.	The artifact is overlapped with EEG data therefor the important EEG data will be lost. A negative spike occur in the background EEG at the artifact spike, and bed filtering when the artifacts lie in the same frequency range of EEG data.
Regression	Simple in implementation, accurate if a reference signal is obtained and the regression process can be in time, and frequency domain	Very difficult to obtain clean reference signal and many assumptions must be satisfied and
Blind source separation	Did not want a priori input; accurately identify the time courses of activation and scalp topographies. The BSS techniques are used also for non-linear domains.	The numbers of sources from brain region are limited to the number of channels in EEG, it is a statistical analysis methods and if the amplitude of artifact is comparable with EEG data then cannot separate
Proposed Method	Advanced statistical algorithms, Evolutionary Wavelet Transform (EWT) algorithm, Wavelet De-noising Technique (WDT), and Band-Pass filtering procedure (BPF). It achieves effective artifact removal while retaining the EEG signals.	Requires a clean reference signal for KF, limited sources from brain regions.

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The scope is expanded in this paper to the comparative study of the output of Wavelet Transform (WT) and Kalman Filter (KF) standard denoising methods. A variety of indexes, such as the signal-to-noise ratio (SNR) and normalized root-mean-square error (NRMSE) are measured to determine the efficiency of WT and KF for noise reduction and to express the quality of EEG. All noise simulated EEG data results show that WT achieved the biggest difference in SNR, as shown in Table 3, which presents the SNR values for the raw signals post the algorithm's application.

Table 3. The NRMSE and SNR measures comparison of EWT and KF.

		EWT		KF	
Measures	Pure EEG	After Rejection	Difference	After Rejection	Difference
NRMSE	0.194088	0.004562	- 0.189526	0.026164	-0.167924
SNR(dB)	-12.790678	6.987598	-19.778276	4.154738	-16.945416

This work successfully employed EWT and KF to extract EOG from EEG. Based on the differences between SNR before and after the rejections, EWT has a small but noticeable benefit, and the signal distortion is a minimum relative to the KF methods, as shown in Table 3. As shown the proposed method can reduce the EOG artifacts to (98.01%) compared to (90.781%) for KF. Table 4 shows the specificity and sensitivity of the proposed method and KF. The evaluation of the count of false positives (FP), true positives (TP), and false negatives (FN), was carried out in comparison with the algorithms.

Table 4. The specificity and sensitivity of the proposed method and KF.

Specificity	Sensitivity	
	EWT	KF
90%	34%	66%
95%	28%	57%
99%	19%	33%

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100 \quad .... \ 12$$

$$\text{Specificity} = \frac{TP}{TP+FP} \times 100$$

As a result, an algorithm might detect a beat without detecting a blink, leading to a false positive (FP); conversely, a false negative (FN) might indicate that the algorithm does not recognize a blink. An accurate detection of blinks is called a true positive (TP).

Conclusion

Wavelet Denoising Technique (WDT), Evolutionary Wavelet Transform (EWT), and Band-Pass Filtering (BPF) are all methods that can be used to remove eye-blink disturbances from EEG recordings. Eye movement in the FP1 channel causes considerable interference to EEG signals. This approach effectively manages this interference. As evidenced by SNR and PSD readings, integration of WDT and BPF with WT leads to improved efficiency.

EEG studies must be trustworthy and precise to yield accurate and reliable results. Eyeblink anomalies are removed using a method that does not distort EEG signals. In this strategy, eye-blinking artifacts are eliminated more effectively than with conventional wavelet transformations. Eye-blinking anomalies are consistently and reliably removed from EEG signals using this hybrid algorithm. Various fields find value in such a significant contribution, including cognitive neuroscience, clinical neuroscience diagnosis, and the development of brain-computer interfaces.

The proposed approach could be tested in numerous research environments, with its real potential for other signal-processing applications to be assessed in subsequent studies. Additional research is needed to improve and augment the algorithm, perhaps by integrating artificial intelligence methods, to boost precision and adaptability. An algorithm was presented in this study that improves the quality and dependability of EEG studies, presenting a tool for researchers and clinicians alike.

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Author's Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Kufa.
- Ethics statement:
  No animal studies are present in the manuscript.
  No human studies are present in the manuscript.
  No potentially identified images or data are present in the manuscript.

Author's Contribution Statement

E. N. A., B. K. H., A. S. A, M. A. A and Z.L. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

References

1. Heyat MB, Akhtar F, Khan A, Noor A, Benjdira B, Qamar Y, et al. A Novel Hybrid Machine Learning Classification for the Detection of Bruxism Patients Using Physiological Signals. Appl Sci. 2020; 10 (21): 7410. https://doi.org/10.3390/app10217410
2. Siddiqui MM, Srivastava G, Saeed SH. Diagnosis of insomnia sleep disorder using short time-frequency analysis of PSD approach applied on EEG signal using channel ROC-LOC. Sleep Sci. 2016; 9(3): 186-91. https://doi.org/10.1016/j.slsci.2016.07.002
3. Höller Y, Helmstaedter C, Lehnertz K. Quantitative pharmaco-electroencephalography in antiepileptic drug research. CNS drugs. 2018; 32(9): 839-48. https://doi.org/10.1007/s40263-018-0557-x
4. Kim CS, Sun J, Liu D, Wang Q, Paek SG. Removal of ocular artifacts using ICA and adaptive filter for motor imagery-based BCI. IEEE/CAA J. Autom Sin. . 2017. https://doi.org/ 10.1109/JAS.2017.7510370
5. Gómez A, Tsanas A, Gómez P, Palacios-Alonso D, Rodellar V, Álvarez A. Acoustic to kinematic projection in Parkinson's Disease Dysarthria. Biomed Signal Process Control. 2021; 66: 102422. https://doi.org/10.1016/j.bspc.2021.102422
6. Noureddin B, Lawrence PD, Birch GE. Online removal of eye movement and blink EEG artifacts using a high-speed eye tracker. IEEE Trans Biomed Eng. 2011; 59(8): 2103-10. https://doi.org/10.1109/TBME.2011.2108295
7. Ghandeharion H, Erfanian A. A fully automatic ocular artifact suppression from EEG data using higher-order statistics: Improved performance by wavelet analysis. Med Eng Phys. 2010; 32(7): 720-9. https://doi.org/10.1016/j.medengphy.2010.04.010
8. Rasheed T, Lee YK. Constrained blind source separation of human brain signals (Doctoral dissertation, PhD Thesis, Department of Computer Engineering, Kyung Hee University, Seoul, Korea). https://doi.org/10.1007/978-3-540-92841-6_136.
9. Ahmed A, Zhu ZC, Yan C. A novel evolutionary approach for blind source separation based on stone's method. IEEE Int Conf Signal Process. 2012; 1: 324-328. IEEE. https://doi.org/10.1109/ICoSP.2012.6491666.
10. Borah BB, Hazarika U, Baruah SM, Roy S, Jamir A. A BCI framework for smart home automation using EEG signal. 2023 (Preprint): 1-9. https://doi.org/10.3233/IDT-220224
11. Jurczak M, Kołodziej M, Majkowski A. Implementation of a convolutional neural network for eye blink artifacts removal from the electroencephalography signal. Front Neurosci. 2022; 16: 782367. https://doi.org/10.3389/fnins.2022.782367
12. Giudice ML, Varone G, Ieracitano C, Mammone N, Bruna AR, Tomaselli V, Morabito FC. 1D Convolutional Neural Network approach to classify voluntary eye blinks in EEG signals for BCI applications. Proc Int Jt Conf Neural Netw. 2020; 1-7. IEEE. https://doi.org/10.1109/IJCNN48605.2020.9207195

13. Mayeli A, Al-Zoubi O, Henry K, Wong CK, White EJ, Luo Q, et al. Tulsa 1000 Investigators. APPEAR recorded during fMRI. J Neural Eng. 2021; 18(4): 0460b4. https://doi.org/10.1088/1741-2552/ac1037
14. Mathe M, Padmaja M, Krishna BT. Intelligent approach for artifacts removal from EEG signal using heuristic-based convolutional neural network. Biomed Signal Process Control. 2021; 70: 102935. https://doi.org/10.1016/j.bspc.2021.102935
15. Krishnaveni V, Jayaraman S, Aravind S, Hariharasudhan V, Ramadoss K. Automatic identification and removal of ocular artifacts from EEG using wavelet transform. Meas Sci Rev. 2006; 6(4): 45-57.
16. Hamdi MM, Mustafa AS, Mahd HF, Abood MS, Kumar C, Al-shareeda MA. Performance Analysis of QoS in MANET based on IEEE 802.11 b. Int Conf Innov Manag. 2020 (pp. 1-5). IEEE. https://doi.org/10.1109/INOCON50539.2020.9298362
17. Al-Shareeda MA, Manickam S. MANETs: Analysis and evaluation. Sym. 2022; 14(8):1543. https://doi.org/10.3390/sym14081543
18. Al-Mekhlafi ZG, Al-Shareeda MA, Manickam S, Mohammed BA, Qtaish A. Lattice-based lightweight quantum resistant scheme in 5G-enabled vehicular networks. Math. 2023; 11(2): 399. https://doi.org/10.3390/math11020399
19. Mohammed BA, Al-Shareeda MA, Manickam S, Al-Mekhlafi ZG, Alreshidi A, Alazmi M, et al. FC-PA: fog computing-based pseudonym authentication scheme in 5G-enabled vehicular networks. IEEE Access. 2023; 11: 18571-81. https://doi.org/10.1109/ACCESS.2023.3247222
20. Al-Mekhlafi ZG, Al-Shareeda MA, Manickam S, Mohammed BA, Alreshidi A, Alazmi M, et al. Chebyshev polynomial-based fog computing scheme supporting pseudonym revocation for 5G-enabled vehicular networks. Electronics. 2023; 12(4): 872. https://doi.org/10.3390/electronics12040872
21. Al-Shareeda MA, Manickam S. COVID-19 vehicle based on an efficient mutual authentication scheme for 5G-enabled vehicular fog computing. Int J Environ Res Public Health. 2022; 19(23): 15618. https://doi.org/10.3390/ijerph192315618
22. Ashraf S, Alfandi O, Ahmad A, Khattak AM, Hayat B, Kim KH, et al. Bodacious-instance coverage mechanism for wireless sensor network. Wirel Commun Mob Comput. 2020; 2020: 1-1. https://doi.org/10.1155/2020/8833767
23. Ahmad A, Ullah A, Feng C, Khan M, Ashraf S, Adnan M, et al. Towards an improved energy efficient and end-to-end secure protocol for iot healthcare applications. Secur. Commun. Netw. 2020; 2020: 1-0. https://doi.org/10.1155/2020/8867792
24. Ashraf S, Ahmed T, Saleem S. NRSM: Node redeployment shrewd mechanism for wireless sensor network. Iran J Comput Sci. 2021; 4(3): 171-83. https://doi.org/10.1007/s42044-020-00075-x
25. Islam MK, Rastegarnia A, Yang Z. Methods for artifact detection and removal from scalp EEG: A review. Neurophysiol Clin. 2016; 46(4-5): 287-305. https://doi.org/10.1016/j.neucli.2016.07.002
26. Zeng H, Song A, Yan R, Qin H. EOG artifact correction from EEG recording using stationary subspace analysis and empirical mode decomposition. Sens. 2013; 13(11): 14839-59. https://doi.org/10.3390/s131114839
27. Valderrama JT, De La Torre A, Van Dun B. An automatic algorithm for blink-artifact suppression based on iterative template matching: Application to single channel recording of cortical auditory evoked potentials. J Neural Eng. 2018 15(1): 016008. https://doi.org/10.1088/1741-2552/aa8d95
28. Kher R, Gandhi R. Adaptive filtering based artifact removal from electroencephalogram (EEG) signals. International Conference on Communication and Signal Processing (ICCSP). 2016; 0561-0564. IEEE. https://doi.org/10.1109/ICCSP.2016.7754202
29. Abdullah AK, Zhang CZ, Lian SY. Separation of EOG Artifact and Power Line Noise-50Hz from EEG by Efficient Stone's BSS Algorithm. Appl Mech Mater. 2014; 543: 2687-91. https://doi.org/10.4028/www.scientific.net/AMM.543-547.2687
30. Singh B, Wagatsuma H. A removal of eye movement and blink artifacts from EEG data using morphological component analysis. Comput Math Methods Med. 2017; 2017. https://doi.org/10.1155/2017/1861645
31. Suja Priyadharsini S, Edward Rajan S, Femilin Sheniha S. A novel approach for the elimination of artefacts from EEG signals employing an improved Artificial Immune System algorithm. J Exp Theor Artif Intell. 2016; 28(1-2): 239-59. https://doi.org/10.1080/0952813X.2015.1020571
32. Dhiman R, Saini JS, Priyanka AM. Artifact removal from EEG recordings–an overview. Proc. NCCI 2010: 1-6.
33. Mowla MR, Ng SC, Zilany MS, Paramesran R. Artifacts-matched blind source separation and wavelet transform for multichannel EEG denoising. Biomed Signal Process Control. 2015; 22: 111-8. https://doi.org/10.1016/j.bspc.2015.06.009
34. Saleh BJ, Saedi AYF, al-Aqbi ATQ, Salman L abdalhasan. Optimum Median Filter Based on Crow Optimization Algorithm. Baghdad Sci J. 2021; 18(3): 0614. http://dx.doi.org/10.21123/bsj.2021.18.3.0614
35. Abbas HK, Al-Saleh AH, Mohamad HJ, Al-Zuky AA. New algorithms to enhanced fused images from auto-focus images. Baghdad Sci J. 2021; 10(18): 1. http://dx.doi.org/10.21123/bsj.2020.18.1.0124
36. Mohammadi Z, Frounchi J, Amiri M. Wavelet-based emotion recognition system using EEG Neural

Comput Appl. 2017; 28(8): 1985-90. https://doi.org/10.1007/s00521-015-2149-8
37. Javidi S, Mandic D, Cheong Took C, Cichocki A. Kurtosis based blind source extraction of complex noncircular signals with application in EEG artifact removal in real-time. Front Neurosci. 2011; 5: 105. https://doi.org/10.3389/fnins.2011.00105
38. Chella F, Pizzella V, Zappasodi F, Marzetti L. Impact of the reference choice on scalp EEG connectivity estimation. J Neural Eng. 2016 X; 13(3): 036016. https://doi.org/10.1088/1741-2560/13/3/036016
39. Hu S, Karahan E, Valdes-Sosa PA. Restate the reference for EEG microstate analysis. arXiv preprint arXiv:1802.02701. 2018 https://doi.org/10.48550/arXiv.1802.02701
40. Sebek J, Bortel R, Sovka P. Suppression of overlearning in independent component analysis used for removal of muscular artifacts from electroencephalographic records. PloS one. 2018; 13(8): e0201900. https://doi.org/10.1371/journal.pone.0201900
41. Egan MK, Larsen R, Wirsich J, Sutton BP, Sadaghiani S. Safety and data quality of EEG recorded simultaneously with multi-band fMRI. PloS one. 2021; 16(7): e0238485. https://doi.org/10.1371/journal.pone.0238485
42. Hossain MB, Bashar SK, Lazaro J, Reljin N, Noh Y, Chon KH. A robust ECG denoising technique using variable frequency complex demodulation. Comput Methods Programs Biomed. 2020; 105856. https://doi.org/10.1016/j.cmpb.2020.105856
43. Wang Y, Fu Y, He Z. Fetal electrocardiogram extraction based on fast ICA and wavelet denoising. 2nd IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC). 2018: 466-469. IEEE. https://doi.org/10.1109/IMCEC.2018.8469501
44. Avendano LE, Padilla JI, Delgado-Trejos E, Cuesta-Frau D. Detection of ECG Fiducial Points Using Recursive Estimation and Kalman Filtering. Comput Cardiol. 2020:1-4. IEEE. https://doi.org/10.22489/CinC.2020.284

القضاء على عيوب وميض العين في إشارات FP1 EEG الأمامية باستخدام تقليل الضوضاء المويجة وترشيح ممر الموجة

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الخلاصة

التحويل المويجي (WT) هو طريقة رياضية شائعة لاستخراج المعلومات من مصادر البيانات المختلفة. ومع ذلك ، عندما يتعلق الأمر بفصل المصدر الأعمى (BSS) ، فقد كان هناك بعض فقدان الإشارة المرتبط باستخدام WT. لمعالجة هذا الأمر ، تم استخدام خوارزمية هجينة تجمع بين ترشيح WT و Bandpass (BPF) لتصحيح الأخطاء. في هذه الدراسة ، تم اقتراح خوارزمية جديدة تستخدم مزيجًا من خوارزمية تحويل المويجات التطوري (EWT) ، والتي تسمى تقنية Wavelet De-Noising (WDT) ، وإجراء تصفية -Band Pass (BPF) للقضاء على رفرفة العين في مخطط كهربائية إشارات الدماغ (EEG). الهدف الرئيسي للخوارزمية هو إزالة إشارات EEG الناتجة عن حركات العين في قناة FP1 للحصول على إشارة EEG موثوقة. توضح النتائج أن هذا التكامل أكثر كفاءة من WT التقليدي ، كما تم تقييمه بواسطة قياسات نسبة الإشارة إلى الضوضاء (SNR) وقياسات الكثافة الطيفية للطاقة (PSD) التي تقيم كفاءة عملية الإزالة.

الكلمات المفتاحية: تحليل الإشارة ، وميض العين ، مخطط كهربائية الدماغ (EEG)) ، عملية ترشيح ممر الموجة (BPF) ، ؛ التحويل المويجي (WT).