OCULAR ARTIFACT SUPPRESSION FOR EEG CLEANING LEADING TO THE BRAIN COMPUTER PARADIGM

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Abstract. Brain Computer paradigm or Interface (BCI) establishes a link between the human brain and the computer where an Electro- encephalography (EEG) signal is data of the human brain. EEG signals are a very popular brain activity recording technique. These EEG rhythms are usually impure due to external and internal noise. Recognizing and eliminating ocular artifacts from an EEG signal is very challenging. Different types of research have already been done on identifying and suppressing ocular artifacts. The proposed method suppresses ocular artifacts from electroencephalography signals, producing an artifact-free, clean EEG signal that gives better accuracy. At first, the fast ICA method is applied, followed by wavelet thresholding and stationary wavelet transform, and finally, the artifact is subtracted from the contaminated signal. It is designed to ensure improved accuracy in ocular artifact removal, but it can also suppress muscular and cardiac artifacts. At first, it was checked on a synthetic signal, and then it was checked on the BCI Competition IV dataset, where it suppressed artifacts successfully. It is feasible to evaluate the suggested method's performance metrics and compare these results with those of the EMD and ICA methods to achieve higher accuracy by computing the ratio of signal to noise (SNR) and average square error (MSE). This research emphasizes ocular artifact suppression and minimal signal loss.

Keywords: Electroencephalography, artifact reduction, ocular artifact, BCI, EMD, ICA

1. Introduction

Around the world, the scientific study of brain-computer interface (BCI), is a very active and expanding topic as it has an impact on medical applications, neuroergonomics, smart environments, neuromarketing, entertainment etc. [1]. BCI is an important research concept because it can create communication between humans and computers for various purposes. By converting physiological information into digital instructions, it is possible to connect the human brain to various peripheral devices without using the muscles and nerves on the outside. The BCI paradigm displays its boundless strength for a strong connection among those who suffer from physical and severe motor disabilities [2, 3, 4]. The current applications of BCIs are grounded in electroencephalogram signals. But the main issue with EEG is its low communication speed and artifacts [5].

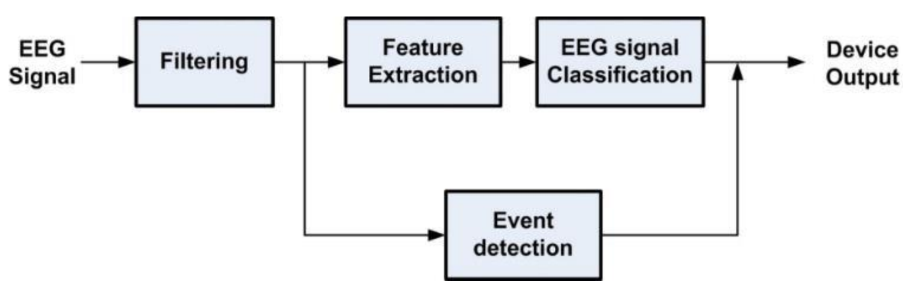

Fig. 1. BCI common structure

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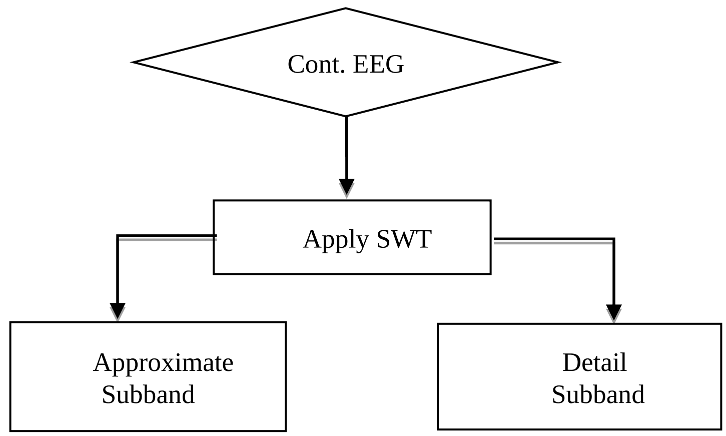

Fig. 2. Block diagram of stationary wavelet transform approach

Electroencephalographic recordings measure the electric impulses of the brain, which are the brain's responses to stimuli. Several brain illnesses are treated and diagnosed using this EEG data. Though the brain recording signals are habitually contaminated by inadvertent artifacts, it is impossible to use these data for clinical applications because of this artifact. This contaminated EEG signal is unusable, and it should be free of artifacts. Ocular artifacts are created by some eye-related activities. Artifacts make it very difficult to interpret EEG signals accurately. It is one of the utmost tasks of brain-machine interconnection to suppress artifacts from the EEG signal. To remove artifacts properly, it is essential to know about their characteristics and nature. The artifact's nature is different from the original signal. It is also necessary to remove artifacts by minimizing data loss from the original signal. Removing artifacts from the original EEG signal is called the preprocessing phase of EEG neural signal processing. The important pre-processing stage for most EEG analyses is the elimination of non- neural source signals from the electroencephalogram. The non-neural signals are familiarized or arrived from the eye. The artifact's nature is different from the original signal, the muscle-related movement, the heartbeat, or other peripheral sources. The elimination of ocular artifacts is a concern in this research. The EOG artifacts are characterized as high-amplitude, low- frequency (below 20 Hz) activity [6]. These EOG signals are naturally instigated by visual activity near the head, such as eye blinking or eye movement.

2. Related Works

To date, several methods have been wished for to remove ocular artifacts, including wavelet transform (WT) [12], principal component analysis (PCA) [11], adaptive filters [9, 10], and an auto-regression-based method (AR) [7, 8]. Using the wavelet transform, the electroencephalogram signal is denoised in three phases. Phases are: first, the signal is split into a predetermined number of stages; second, the detail values are thresholded; and finally, the signal is recovered using the filtered representation. The wavelet breaks down the sources of the detected signal based on the WT to eliminate artifacts. [13].

The DWT technique is frequently guided by choosing threshold conditions, for example, Stein's unbiased risk estimate (SURE) [14]. It is also executed in [13] or in additional thresholding systems [15] to ensure that only adequate factors are reserved. However, the DWT remains a fascinating method for EEG signal processing on its own [16, 17, 18, 19]. In the present day, it is usually found in a collective process with other denoising methods like ICA. [20], one of the main causes of the DWT's inability to completely remove non-neural signals that interfere with neural signals in the spectral region, such as ECG or EMG signals, is that these signals are present in the spectrum [21].

To assist categories' artifacts, the WT has been selected here. It is also appropriate for the study of non-stationary neurological signals, like EEG signals. The wavelet is also an effective tool for classifying unexpected oscillations or limited activities, typically caused by visual distortions. [22]. Compared with continuous transforms for wavelets, the DWT is the easiest method, considering computational or time complexity. Until now, the difficulty of DWT has been that it is a translation variant. As a result, subtle changes in a signal can have significant effects on wavelet coefficients and the way energy spreads across various wavelet scales [23, 24]. As a result, non-neural signals are frequently familiarized during signal reform by denoising with DWT in the neural signal's nearby incoherence. Translation invariance characterizes the stationary wavelet transform (SWT). So, this is the one solution to using the SWT algorithm, as there is no decimation of data in the algorithm [23, 24]. Although it has redundant data and is comparatively slow, it overcomes the translation invariance drawback of DWT.

In current years, various conventional approaches, like average artifact regression analysis [25], principal component analysis (PCA) [26], and ICA [27, 28, 29], have been extensively used to get rid of ocular artifacts from multiconnection EEG signals. In the initial method, the conductivity of the electrode collecting the electrooculogram signal and the properties of the other electrodes were found to behave similarly. The relationship between the EOG channel and other EEG channels is then rated based on conductivity, and the EOG signals are then removed from each EEG channel. On the other hand, in the PCA method, the electroencephalogram and electrooculogram signals want to capture the recording all at once throughout the testing, and the artifacts are eliminated by evaluating the key elements. Principle component analysis (PCA) and ICA, a linear transformation method, assume that the EEG signal is a direct mixture of statistically self-determining sources. The ICA approach, which differs from the primary methodology, obtains a separately independent source signal and splits the characteristics exclusively according to their statistical aspects. That also happens for the practical signal when the parameters of the source signal and transmission channel are unknown [30].

A fusion approach for EEG signal preprocessing has been suggested [40] to reduce artifacts in the EEG in BCIs. The following actions are part of the fusion process: First, the enhanced FastICA method divides the raw EEG signals into a collection of statistics-independent components (ICs). The modified empirical mode decomposition method (EMD) is then used to deconstruct each independent component into a set of intrinsic mode functions (IMFs). IMFs with high-frequency noise are frequently eliminated. The remaining IMFs are rebuilt. The enhanced FastICA algorithm's iterative procedure also significantly reduces artifacts, after which inverse ICA is used to reconstruct the EEG signals. Finally, the cleaned EEG signal was acquired. The comparative experiment demonstrates that the EMD-ICA fusion algorithm not only accurately removes the artifact components but also better preserves the local properties of the raw EEG. In order to preserve neural information, artifacts were eliminated using a combination of well-known conventional classifiers and the stationary wave- lets transform (SWT) [41]. The paper [43], described several artifact removal methods and their limitations. To create new SPTs, more studies will be needed, such that they can handle severe motion artifacts during ambulatory recordings, enable online/real-time analyzing, permit on-chip operation (if appropriate), work with cloud computing, store and use the recorded big data for useful decision-making, and, most importantly, can be customized for various applications and/or various biosignal formats. A Comparison of several signal-processing techniques for removing EEG artifacts is listed in Table 1.

The paper proposed a hybrid method. The planned method is the combination of SWT and the denoising technique ICA that is applied in this paper to remove ocular artifacts. This article compares this hybrid method with different existing techniques. The paper specifically compares the removal of ocular artifacts from single-linkage EEG data using EMD, ICA, and this intended approach. Additionally, it is necessary to demonstrate and assess the approaches' efficacy in eliminating eye blink artifacts using two performance indicators. This paper compares different artifact removal techniques with the proposed method. With regard to ocular artifact removal from single-channel EEG data, we specifically discuss empirical mode decomposition (EMD), independent component analysis (ICA), and the projected technique. Furthermore, the research presented and evaluated the methods' ability to remove eye blink artifacts by means of two performance metrics. The paper is organized as follows: In Section II, various methods (EMD, SWT, and ICA), including the one that is suggested, are described. Section III contains the experimental findings and a discussion of the artificially contaminated EEG data and performance metrics. Section IV concludes this work.

3. Methods

3.1 The Datasets

To evaluate the effectiveness of the proposed approach, the BCI Competition IV 2a and 2b datasets are utilized in this re- search paper. It is experimented with and gets a better result from it. Here, the dataset is listed below.

Brain-Computer Interface (BCI) Competition IV-2a dataset

- bciciv_2a_sub8_left_hand.mat
- bciciv_2a_sub8_right_hand.mat
- bciciv_2a_sub9_left_hand.mat
- bciciv_2a_sub9_right_hand.mat

Brain-Computer Interface (BCI) Competition IV-2b dataset

- bciciv_2b_session2_sub2_left_hand.mat.
- bciciv_2b_session2_sub2_right_hand.mat.

The EEG is crucial for capturing the electromagnetic signal of the human brain, and it must guarantee that the data it produces is accurate and useful. The EEG data is used for further application. Artifact-free EEG data can give better output in any field and can help make decisions effectively. So, it is necessary to make sure that this EEG data is artifact-free. Ocular artifact suppression for EEG is a great matter of concern in EEG signal processing. Ocular artifacts can be located on the front electrodes (FP1, FP2). The Fp1 and Fp2 (frontoparietal) electrodes next to the eyes experience a change in potential as the eyes and eyeballs move. Fluttering, eye blinks, and eye movement are created artifacts. There are some methods of artifact removal such as regression analysis (RA), blind source separation (BSS), empirical mode decomposition (EMD), the Fourier transform (FT), the wavelet transforms (WT), etc. Some methods are applied manually, and some are applied automatically.

So, this research proposed an innovative method that can suppress EOG artifacts from a noisy EEG signal, clean the EEG signal, and give better accuracy, which is validated by the signal's statistical properties and by calculating the mean square error (MSE) and signal-to-noise ratio (SNR). This proposed method successfully suppresses ocular artifacts and gives an artifact-free, clean EEG signal leading to a brain-computer interface.

3.2 Empirical Mode Decomposition (EMD)

A signal-denoising technique appropriate for processing non-stationary and non-linear series is empirical mode decomposition. It performs an operation that partitions a series into modes called Intrinsic Mode Function (IMF). It’s a popular time- space study method called the identical Fourier transform, also known as wavelet decomposition. The energy calculation for the intrinsic mode function (IMF) is high. In EMD, ocular artifacts are found in higher-energy IMFs. It is applied for com- parison purposes and statistical analysis of the EEG signal [23]. On the basis of the empirical mode decomposition (EMD) method [9], the signal s(t) is characterized as:

$$s(t) = \sum G_g(t)\, P_g(t) + q_G(t) \tag{1}$$

where, $p_G(t)$ is the intrinsic mode functions (IMFs) obtained from the signals, and $q_G(t)$ is residue with negligible energy. Here, G is the total number of IMFs. The fullness of the decomposition is given by Eq. (1). For comparison purposes, the clean EEG signal using the EMD method is plotted in fig. 5.

3.3 Stationary Wavelet Transform (SWT)

The stationary wavelet transform is the name given to the undecimated DWT. The decimators are not used in this wavelet transform following the low-pass or high-pass filters. This technique does not down-sample, therefore it does not lose any time-related information and definitely exhibits shift-invariance. Because of the oversampling that SWT showed, it has good time resolution at low frequencies and consistently generates smoother results. Because there is no down-sampling, it also never suffers from aliasing. The fundamental distinction between the DWT and SWT schemes is the filter at each stage. The low-pass and high-pass filter sequences, which are the same length as the original design, are derived at each level of decomposition from approximate and detailed portions shown in fig. 2. After identifying the factors at the level, the technique samples the filter coefficients by a factor of [31]. It is highlighted that the level dependence of the individual reconstruction filter As a result, each filter coefficient has zeros. These procedures are iteratively continued until recovering the main signal. In this way, two kinds of coefficients are produced: approximate and detail coefficients that cover short and lengthy frequency facts separately. Then generated wavelet quantities at various stages represent the correlation coefficients between the artifactual signal and the usage wavelet function. The larger coefficient values are obtained from corrupted components if they contain a greater correlation through the wavelet function. On the other hand, the lesser coefficients will be produced, corresponding to the real neuronal actions. The MATLAB software's swt function has implemented the artifact-removing approach utilizing SWT, and the db4 mother wavelet is utilized in this paper.

For SWT, the length of the input signal is multiple of $2L$ where L be levels and put on swt function in input signal. Later breakdown of input signal, the decomposition level length and the main signals are in identical. The EEG input signal under examination can be written as:

$$x(t) = \sum_{n=1}^{L} q_n(t) + q_1(t) \tag{2}$$

Where x(t) is a signal input, L is the level, q_1 are the n^{th} and L^{th} subbands corresponding to the detail and approximate coefficients separately [8]. Subsequently when the decomposition process is completed, the first signal is represented by:

$$x'(t) = \sum_{n=1}^{L} q_n(t) \tag{3}$$

A decent separation of signal and noise depends on the wavelet basis and how similar it is to the source signals, as shown by the explanation above and the equation that follows. As a result, the noise elimination technique's strategy depends on the mother wavelet rescaling, the reduction rule, and the noise depth [13].

3.4 Independent Component Analysis (ICA)

Independent component analysis (ICA) is a method for obtaining the characteristics of independent components. Actually, the components that makeup ICA are separate from one another. The ICA method retrieves crucial characteristics from these parts. Blind source separation is ICA's most important application. This helps distinguish between independent impulses, brain signals, and noise. To detect and eliminate anomalies in the eye, muscles, and line noise, ICA is frequently employed in EEG research [42]. The approach of extracting characteristics from MI EEG recordings using ICA is employed sporadically.

A computational technique called independent component analysis is used to separate or extract relevant components from the noise in brain input. It is an extremely well-liked technique for separating multichannel sources. It uses the blind source separation method to operate. Assuming that the sources S1, S2, and S2 have merged, the ICA method is used to separate the signals based on the sources. Neuronal EEG data are examined using the independent component analysis (ICA) technique. The ICA contains a random vector that reduces the statistical requirement among the signal's mixed components when looking for a linear transformation. Few artifacts restrict the interpretation and analysis of clinical EEG signals when they are utilized in practice. As a result, the unclean EEG regions that were deleted cause unwanted information leakage. In that study, the ICA methodology was developed based on the EEG data collected during certain exercises, which accurately identified self-directed source components that could be employed with other signal-processing techniques [32]. ICA has the ability to reduce EEG signal artifacts through the use of signal preprocessing techniques. When a multi-channel signal is recorded, its advantages are immediately apparent to us. In order to enhance both the true brain signal and artifacts in different components, the ICA approach rearranges the independent sources to produce innovative combinations in this way.

Let S = [S1, S2, SM] represent the statistically distinct source signals. An indefinite matrix A is linearly mixed with the signal S to form the n-dimensional observation signal, $X = [X_1, X_2, ... X_N]$. In order to identify a linear transformation separation matrix W to make the output signal as close to S as possible, the ICA technique relies on the presumption that X and S are statistically independent because both A and S are unknown. The Fast ICA [36] approach may sequentially separate independent sources because it has been selected to search in the direction with the biggest negative entropy. The use of fixed-point repetition accelerates and strengthens convergence. In order to extract the source signal S, we process the subband using this method. The EEG signal, which is produced by the bioelectrical activity of the brain, provides a wealth of physiological and pathological information. Furthermore, the EOG signal only distinguishes between blinking and ocular movement. EEG signals showed more complex features than EOG signals. As complexity rises, so does the entropy that reflects it. The resulting extremely entropic EEG signals can be used to extract the components. A mixed signal that combines a defined signal with a random signal may be computed using the sample entropy since it approximates the time-domain statistical characteristic more accurately than the approximate entropy [37, 38].

4. Proposed Algorithm for Artifact Separation

Electroencephalograms (EEGs), which are produced by pinning many sensors to the scalp, are used to visualize the electrical activity occurring in the brain. EEG signals are complicated in nature and can contain a number of artifacts, such as ocular, cardiac, muscular, etc. The process of removing artifacts from EEG data can be thoroughly studied by presuming that the artifacts are of the additive white Gaussian noise (AWGN) kind. Because of its capacity to remove abnormalities from the signal, ICA is used to reorganize the source signal into two mixtures in such a way that the brain signals and the artifacts get separated, despite the restriction that it can only be used on multichannel signal input. In order to remove noise from the EEG signals in this case because the input EEG is a single channel, ICA is combined with the stationary wavelet transform

(SWT). A quantitative evaluation of the proposed method has been conducted using the signal-to-noise ratio (SNR) metric, which demonstrates appropriate filtering at various AWGN intensity levels.

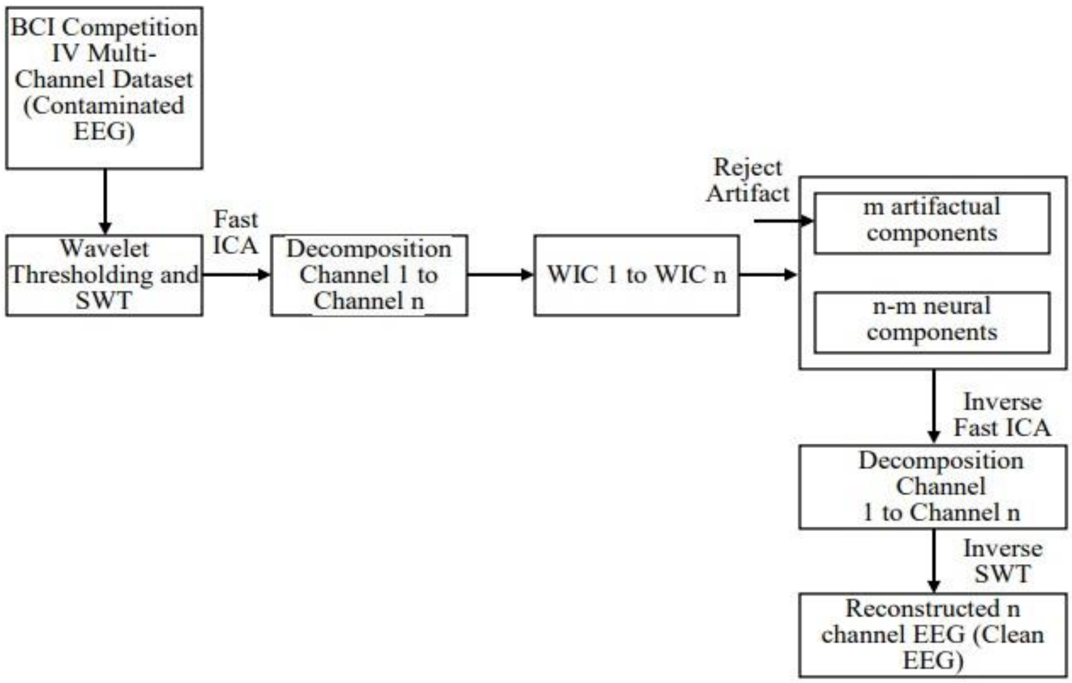

Fig. 3. Proposed method for MI EEG signal cleaning using stationary wavelet transform (SWT) artifact removing method

The recommended method in fig. 3 presents a novel approach for automatic EEG artifact removal by combining wavelet thresholding and quick independent component analysis. Fast independent component analysis (FICA) should be used to obtain the n-channel ICs from a polluted EEG signal, and wavelet thresholding should be used to exclude low-amplitude activity from the computed ICs. This is helpful for separating the artifact-only ICs from the original EEG data and then deleting the artifact reconstruction. The following illustrates how the suggested method might operate:

Step 1: Perform fast ICA on a contaminated signal to get n channel ICs and n*n mixing matrices (A), where matrix (A) is the inverse of (W) and separating matrices (W) are the inverse of (A). In this step, data whitening is also performed.

Step 2: Perform thresholding and stationary wavelet transform (SWT) to get automatic threshold values for n-channel ICs. For getting automating threshold value for every ICs and performing wavelet transform the data have to be padded. In the proposed method, the wavelet family = "coif5" and decomposition level = 5 is used.

Step 3: Perform an inverse wavelet transform on artifactual coefficients to get modified n-channel ICs.

Step 4: These n-channel modified ICs (mICs) are multiplied by the n*n mixing matrix (A) for ocular artifacts. To get the ocular artifacts, the mICs are multiplied by a mixing matrix. For n-channel ocular artifacts = (n-channel mICs) * (mixing matrix A). Finally, ocular artifacts = mICs * A.

Step 5: As the artifact zone is identified, the task is to suppress artifacts from the contaminated EEG signal. Now getting the clean EEG signal, then subtracted the ocular artifacts from the n-channel contaminated signal. So, Sup- press ocular artifacts = n channel contaminated signal - n channel ocular artifacts. And finally, Clean EEG = Contaminated EEG – Ocular Artifacts.

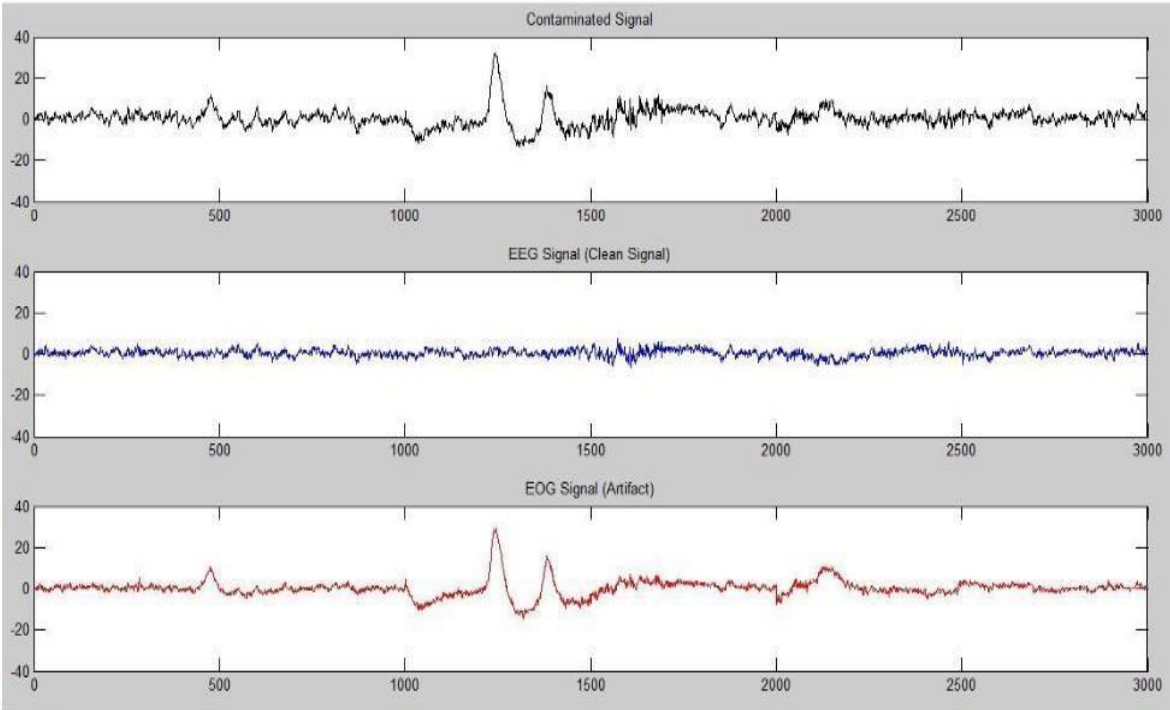

Fig. 4. Contaminated EEG signal, clean EEG, and EOG signal for the proposed method.

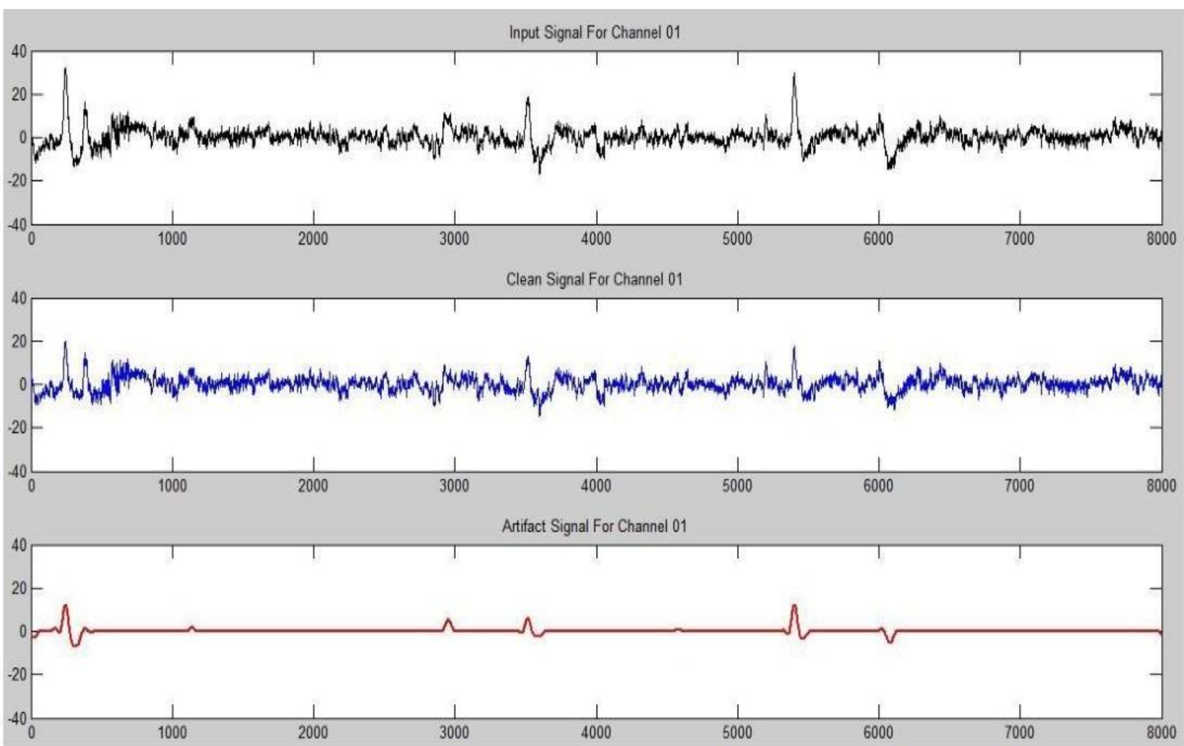

Fig. 5. Artifact suppression using the EMD method for real EEG signal

4.1 SWT-ICA Method

In this paper, the SWT-ICA joint algorithm is used to denoise the EEG signal. The proposed method works effectively in the MATLAB programming language and numeric computing environment for EOG suppression. The algorithm steps are as follows:

Algorithm-1: Implementation process for EEG Cleaning [Robust artifact suppressed method]

Input: Real EEG data from BCI Competition IV-2a and 2b dataset

Output: Artifact free clean EEG signal

1: Choose and load the .mat file for an input real EEG data, S
2: Apply wica.m function for wavelet enhanced Independent Component Analysis
3: Check inputs (e.g. matrix format data, Set parameters: wavelet level, wavelet name, etc.)
4: Apply fastica.m function to get independent artifactual epochs or components (ICs) and others [IC, A, W] from EEG data.
5: Calculate [A, W]=fpica, fixed point algorithm
6: Calculate PCA.m and whitening data
7: Apply inverse fastica.m function
8: Use 'ddencmp' MATLAB function as wavelet-based denoising to assist in determining the denoising parameters
9: Apply wavelet thresholding to determine the automatic threshold value for each IC using the thresh that we get from the ddencmp.m function.
10: Multiply the threshold by a scalar as thresh=thresh*mult
11: Use stationary wavelet transform swt function to wavelet transform the ICs.
12: Compute Y=wthresh to threshold the wavelet to remove small values
13: Compute wic(s,:)=iswt(Y, wavename) to perform inverse wavelet transform to reconstruct wavelet independent components (wICs)
14: Repeat steps 8 to 12, n times until get the n values of wICs
15: Apply if~ isempty (extra) wIc=wIC() end to remove extra padding.
16: Repeat steps 13 and 14 to get [wIC, A] =wICA (data, [], 8, 0)
17: Multiply modified wICs by mixing matrix A to get the artifact as follows:
Artifacts, Sn(t)=wICA*A;
18: Use formula-4 to process the clan EEG signal X(t)= S(t)- Sn(t)(4)
19: Plot the clean_EEG signal and artifact_signal.
20: Calculate Signal-to-Noise Ratio (SNR) and Mean Square Error (MSE) for measuring performances.
21: Exit.

Thus, the proposed method works effectively as a detection, denoising, and reconstructing method for EOG suppression.

5. Results of the Experiment and Discussion

In this part, the suggested method is evaluated using an EEG signal that has been intentionally damaged. The signal is then composed using EMD and ICA. The time series of polluted EEG data is divided into several subbands using the proposed technique, EMD, and ICA, for comparison purposes. The proposed EMD, ICA, SWT-ICA, and other potential multiresolution decomposition methods are capable of evaluating non-stationary signals like EEG. With a 5-level decomposition, "coif5" is used in this investigation. It is an additional method for reducing EOG artifacts. The EMD, ICA, and SWT-ICA-based filters are used to obtain artifact-free EEG. fig. 2 shows how the threshold subband is selected using the subband energy. The pure EEG of that channel is separated using Eq (2) after obtaining the index of the threshold subband (for the EEG channel). Here, the subband breakdown of electroencephalography recordings is not provided. It is possible to obtain the purified electroencephalography, which accurately depicts brain activities, by removing the electrooculogram from the raw electroencephalography.

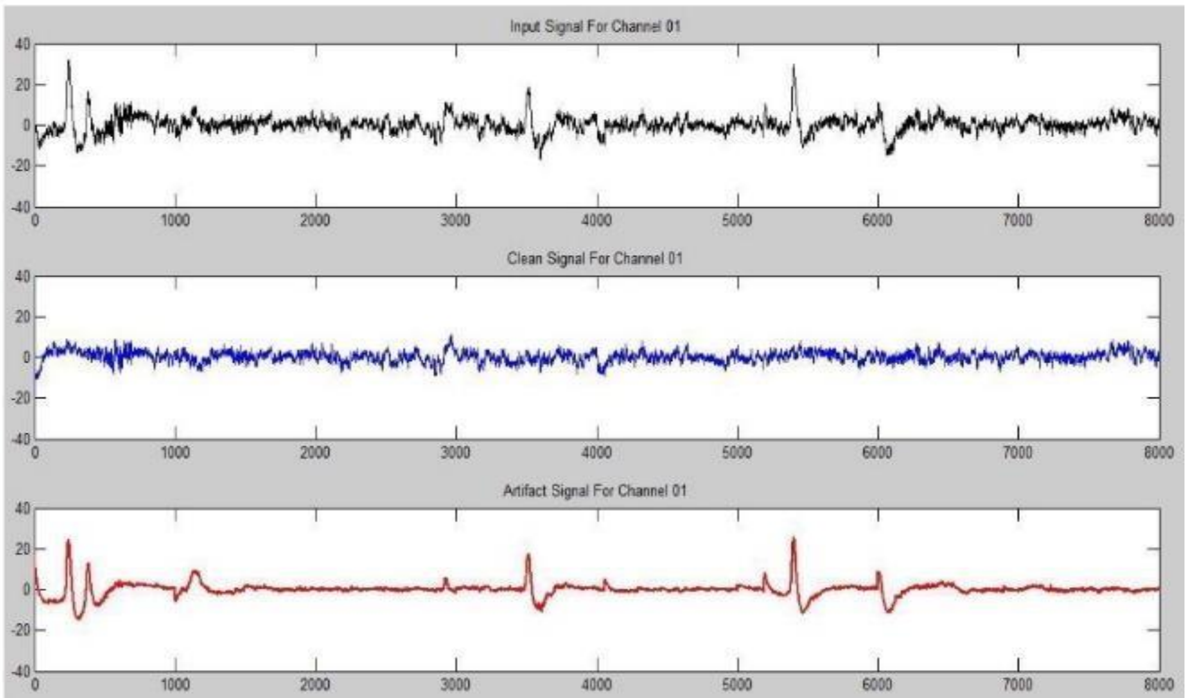

Fig. 6. Artifact suppression using the ICA method

In fig. 4, the top portion shows an artificially contaminated EEG signal, the middle part indicates a clean EEG that is separated by the proposed SWT-ICA method, and the bottom part of this figure shows the separated artifact EOG signal. Fig. 5 through fig. 7 shows the first raw, real contaminated EEG, the second raw, clean EEG obtained by EMD, ICA, and the proposed method, respectively, and the third raw, indicated artifact of the EEG signal.

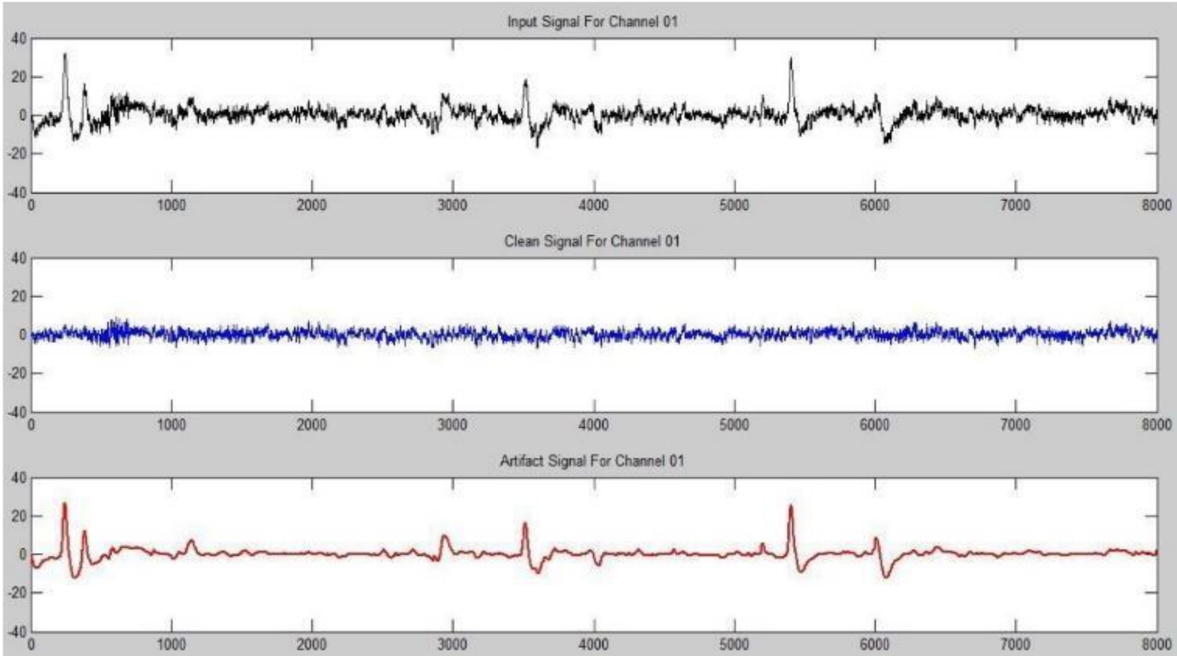

Fig. 7. Artifact suppression using the proposed method

5.1 Compare the Proposed Method with the Existing Artifact Suppression Method

The electrooculogram suppression findings for one channel of electroencephalography data are shown in fig. 8 the first, second, and third rows, respectively, show the separated electrooculograms for EMD, ICA, and SWT-ICA. Fig. 8 shows that more original information is present in the extracted EOG obtained using the EMD approach compared to the ICA and SWT- ICA methods, which have eliminated the artifacts. It is obvious that when employing EMD for artifact reduction, base EEG or lower frequencies of brain data may be lost. ICA and SWT methods are employed to lessen data loss. It also shows the dirty and polluted EEG for the three procedures. This figure shows that the SWT-ICA-based method is the most effective at reducing the EOG that can be created from polluted EEG without affecting the data and can be used to create clean EEG. Pure EEG doesn't show any discernible EOG. The presented method demonstrates that the purified EEG signal is completely free of artifacts.

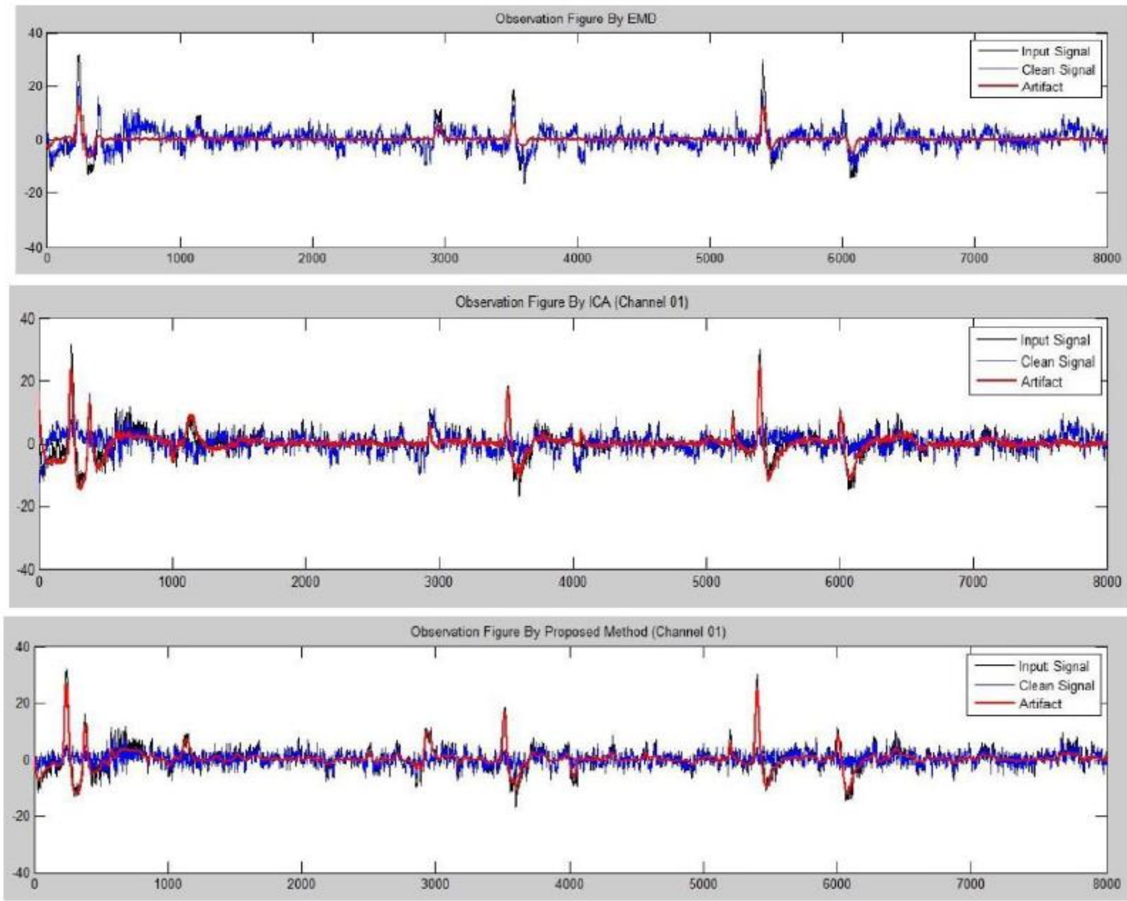

Fig. 8. Artifact suppression using different artifact removal and the proposed method on the same data (BCI competition IV 2b)

5.2 Performance Metrics

Two performance measures, including the signal-to-noise ratio (SNR) and mean square error (MSE), are used to evaluate the method's effectiveness in reducing ocular artifacts from EEG. Two criteria are used to validate the suggested method. They are as follows:

Signal-to-noise ratio (SNR)

SNR is the abbreviation for signal-to-noise ratio. It is mostly self-explanatory; therefore, it wouldn't need much explanation. Simply put, it is the signal-to-noise power ratio as shown mathematically below [33].

$$SNR = \frac{\overbrace{P_{signal}}^{\text{Wanted component}}}{\underbrace{P_{noise}}_{\text{Unwanted component}}}$$

As illustrated below, SNR can be expressed graphically.

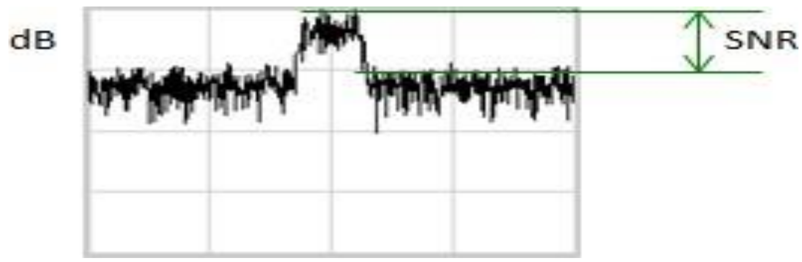

Fig. 9. Graphical representation of SNR

If SNR is represented on a dB scale, it can have either a positive or negative value. Validating the EEG system's performance is essential for ensuring its dependability. To demonstrate that performance may be evaluated using standardized metrics, a variety of performance measurements are used [34]. SNR, or signal-to-noise ratio, is employed for validation. Definition of signal-to-noise: [35].

$$SNR = 10 \times log10\ (P_{\text{signal}})\text{z} / P_{\text{noise}} \tag{4}$$

The proposed method's signal-to-noise ratio is -2.4620, which is higher than that of existing methods and yields superior results.

Mean Square Error (MSE)

One number that indicates how well the regression line fits the data is the mean squared error. The MSE value should be as low as possible because lower values indicate smaller magnitudes of error [33]. The mean square error was used in this study to compare the performance and efficacy of the suggested method and traditional methods. The definition of mean square error

$$\text{MSE} \ = \frac{1}{n}\sum_{i=0}^{n}(y_i + y'_i)^2 \tag{5}$$

In this case, indicates contaminated EEG, denotes the estimated signal de-noised by EMD, ICA, and the proposed technique, and n denotes the length of the signal or the number of samples. And the procedure for removing the artifact is better the lower the MSE value. It refers to how closely the original signal and the de-noised signal resemble each other. The proposed method's mean square error (MSE) is 9.0204*e-34, which is extremely tiny and close to zero. That improves the outcome of the suggested method. It illustrates the variance between the original and updated signals [5]. The MSE of the cleaned signal is greater in accuracy than the MSE of the noisy signal.

Table 1. An overview of how the suggested method compares to other existing techniques

No.	Methods	SNR (dB)	MSE
1.	EMD [23]	0.6883	$2.9878 \times e^{-31}$
2.	DWT [23]	-5:3210	$2.2517 \times e^{-31}$
3.	SSA [39]	-6:0421	$3.0352 \times e^{-29}$
4.	ICA [40,42]	-4.2487	$3.1368 \times e^{-32}$
5.	SWT [41]	-4.70 10	$2.2651 \times e^{-31}$
6.	Proposed	-2.4620	$9.0204 \times e^{-34}$

Table 1 compares the SNR and MSE values obtained from the EMD, ICA, and proposed methods, respectively. The tables demonstrates that the EMD and ICA-based techniques produce results with SNRs of 0.6883 and -4.2487 dB, respectively, which are lower than those of the proposed method and can remove more artifacts. SNR for the ICA is -4.2487 dB, while SNR for the suggested approach is -2.4620dB. In comparison to EMD and ICA, the proposed technique has a reduced MSE value. The MSE and SNR results demonstrate that the "coif5" mother wavelet-based technique is able to filter out more noise than EMD and ICA. From Table 1, it is clear that our suggested strategy outperforms other existing methods in terms of SNR. Hence, we can conclude that the suggested method has a higher suppression capacity than current methods. In addition, the MSE is determined, which is the least of any approach now in use. Also, it is found that the proposed method has greater suppression capability than existing methods after analyzing it using two parameters, MSE and SNR. Therefore, it is believed that suggested strategy can significantly advance the brain-computer interface. For additional feature extraction and classification leading to a brain-computer interface, it must have a clean EEG signal and artifacts.

6. Conclusion

Three different artifact-removing approaches have been described in this paper so that their effectiveness in getting rid of the artifact may be evaluated. Using EMD, ICA, and SWT-ICA, it was able to implement the plan of eyeblink artifact sup- pression from contaminated EEG signals. The electroencephalography signal, or EOG, is regarded as the trend of the signals. For real-time systems, rapid algorithms are necessary. It is well recognized that for real-time analysis, DWT and LWT are faster procedures than SWT and use fewer computer resources. SWT is suitable for applications where computing speed is not a major concern. Performance measurements show that the lifting wavelet transform outperforms the other two artifact- removing techniques in terms of removing noise while maintaining neural signals. Our forthcoming study will focus on feature extraction, motor imagery categorization, real-time ocular artifact removal, hardware execution for ocular artifact removal for a single channel EEG approach, and monitoring based on brain activation in a natural setting using a wearable embedded system. This paper presents a critical analysis of existing artifact removal methods and their criticisms. By combining wavelet thresholding with ICA, a unique method is developed in this study for automatically identifying, eliminating, or reducing ocular artifacts from EEG signals. Using simulated and real EEG datasets, the usefulness of the suggested strategy was illustrated. In comparison to two established approaches from the literature, the performance and efficacy of the suggested method are examined. Regression, ICA, and REGICA approaches did not perform as well as the suggested method, according to efficient ocular activity reduction and neural signal retention. The MSE is also used to calculate the effectiveness of the suggested strategy in the time domain. Another factor is the SNR, which has been calculated for validation criteria. Ocular artifacts cannot be denied because eye movement and brain signals are interrelated to each other. There are so many related works that are being applied for artifact removal, and they are effective from different perspectives, but the proposed method gives better performance with minimum signal loss. Empirical mode decomposition and independent component analysis are compared with this method, and the proposed method gives a better result in ocular artifact suppression than these. Empirical mode decomposition takes longer processing time, and the energy calculation of the intrinsic mode function is high. Independent component analysis originating from blind source separation can sometimes cause a loss of real data, and this is not suitable for real-time artifact removal. The proposed method is a novel enhanced method that gives us better accuracy in ocular artifact removal with minimum data loss. It is applied to a multichannel EEG dataset. It was challenging to remove artifacts from more than one channel. The future direction of this research is to apply this clean signal for feature extraction and classification purposes.

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