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Automatic Eyeblink Artifact Removal from EEG Signal Using Wavelet Transform with Heuristically Optimized Threshold

Souvik Phadikar, *Student Member, IEEE*, Nidul Sinha, *Sr. Member, IEEE* and Rajdeep Ghosh

***Abstract*— This paper proposes an automatic eyeblink artifacts removal method from corrupted-EEG signals using discrete wavelet transform (DWT) and meta-heuristically optimized threshold. The novel idea of thresholding approximation-coefficients (ACs) instead of detail-coefficients (DCs) of DWT of EEG in a backward manner is proposed for the first time for the removal of eyeblink artifacts. EEG is very sensitive and easily gets affected by eyeblink artifacts. First, the eyeblink corrupted EEG signals are identified using support vector machine (SVM) as a classifier. Then the corrupted EEG signal is decomposed using DWT up to the sixth level. Both the mother wavelet and the level of decomposition are selected using appropriate techniques. Then the ACs are thresholded in backward manner using the optimum threshold values followed by inverse DWT operation to reconstruct the original EEG signal. The AC at level 6 is thresholded and is used in IDWT with DC to get back the AC at level 5. Likewise, the backward thresholding of the ACs followed by IDWT is continued till the artifact free EEG signal is reconstructed at level 1. The optimum values of the thresholds of the ACs at different levels are optimized using two meta-heuristic algorithms, particle swarm optimization (PSO) and grey wolf optimization (GWO) for comparison. The results reveal that the proposed methodology is superior to the recently reported methods in terms of average correlation coefficient (CC) which states that the proposed method is better in terms of the quality of reconstruction in addition to being fully automatic.**

***Index Terms*— Artifacts, DWT, Electroencephalogram, GWO, NMSE, PSO, SSIM, Thresholding.**

I. INTRODUCTION

BRAIN Computer Interface (BCI) is an intelligent system that creates a direct communication path between the human neuronal system and external devices by directing human intentions into control signals. The EEG is the most widely used system to extract brain responses for BCI systems due to its fast and dynamic processing and high temporal resolution [1]. EEG is a measure of the brain's electrical activity as sensed by the electrodes placed non-invasively on the scalp. It is an indication of the accumulative electrical activities of neurons. On the other hand, EEG is also used for the diagnosis of various brain disorders, like epilepsy, Alzheimer's disease, etc. by neurologists. Today, EEG is attracting interest of researchers in human emotion recognition system, attention monitoring etc. EEG signal is very random in nature, and its non-stationary characteristics opens a wide range of research in EEG signal processing.

S. Phadikar, Research Scholar, Department of Electrical Engineering, NIT Silchar, Assam, India.(souvik.phadikar@gmail.com)

N. Sinha, Professor, Department of Electrical Engineering, NIT Silchar, Assam, India. (nidul.sinha@gmail.com)

R. Ghosh, Asst. Professor, Department of Information Technology, Guwahati University, Guwahati, Assam, India. (grajdeep.2014@gmail.com)

Even though EEG is designed to monitor cerebral activity, electrical activities from sources other than the brain corrupt the EEG. Those recorded non-cerebral activities are referred to as artifacts. Such kind of artifacts occur in the EEG signal due to eyeblink, eye movement, muscle movement etc. of the subject. These artifacts usually contaminate the EEG signals, making it difficult to extract information from EEG signals for BCI applications as well as in medical diagnosis. For processing and analysis of EEG signals for the identification of diseases related to the human brain, the artifacts should be removed from the original signal. The artifacts may be present in EEG signals in all electrodes but not necessarily in the same proportion. The eyeblink artifact occurs as a result of eyeblink by the subjects. It is often dominant over other artifacts and contaminates the original signal by producing artifacts of very high amplitude. The frequency of eyeblink artifacts ranges from 0.1 to 3Hz, and removal of such low frequency artifacts from the EEG signal is a broad research area in signal processing. Low frequency noise removal is challenging and very risky procedure because of the chances of loss of information inherent in the EEG signal.

Wavelet thresholding is one of the most efficient noise removal methods in signal processing. Wavelet thresholding technique to remove artifacts consists of three major steps: 1) wavelet decomposition, 2) thresholding wavelet coefficients, 3) wavelet reconstruction to get back the original signal free of noise. It is well known that the high frequency components are preserved in DCs, while low frequency components are preserved in ACs. Hence, the thresholding of ACs may result into removal of eyeblink artifacts better. Earlier the threshold was chosen arbitrarily which failed to remove artifact effectively and automatically [2]. To solve this problem, a universal and statistical threshold formulation was proposed in the literature which consists of a constant scalar value which may vary with the data [3]. Hence, it needs visual inspection, which makes it unfit for online and automatic removal of artifacts.

Several denoising methods have been developed to remove the artifacts from the original EEG signals [1], [2], [4]. Artifact rejection is the simplest strategy which rejects epochs comprising of artifacts. However, artifact rejection is very laborious and time consuming process and often results in significant loss of information from available data for analysis [1]. An eye fixation method in which subjects are asked to fix their eyes either in close or in open is unrealistic [1]. In previous traditional methods, linear filters and regression based analysis are used to remove the artifacts from the corrupted signals [5]. However, filtering process in either time domain or frequency domain results in considerable cost of physiological activities because of intersection of brain activity and artifacts in the spectrum of corrupted EEG signal [6]. All time or frequency based regression methods depend on having extra one or more regressing channel and suffer from a fundamental weakness that the range of eyeblink activity and EEG signal is bidirectional [7]. Wavelet transform based analysis is shown in the literature to be more efficient for erasing artifacts, while maintain the true shape of the original EEG in both time and frequency domains [8], [9]. In the literature, independent component analysis (ICA) is widely used for removing artifacts from EEG signal, which was refined with regards to blind source separation (BSS) issues to get independent components (ICs) [10]. With the assumption that the signals are linear mixtures of cerebral and artifactual sources, ICA can decompose an observed signal into ICs and the components pertaining to the artifacts are eliminated from the mixtures to remove the artifacts from the original signal. However, all ICs may contain cerebral activity, and hence eliminating one or more of them may cause significant loss of information. In recent years, several hybrid methods, such as combination of wavelet and ICA, BSS and adaptive filtering have shown promising results in real time applications.

Several methods have been discussed in the literature, including the methods such as adaptive filtering, discrete wavelet transform (DWT), the combination of wavelet and ICA, Ensemble Empirical Mode Decomposition (EEMD) and ICA etc. He. *et al.* [11] proposed an adaptive filtering based method to correct ocular artifacts (OA). The method achieved good performance in cleaning the EEG signal but it required an extra reference channel to estimate the OA. Krishnaveni *et al.* [12] proposed an automatic wavelet thresholding based denoising to correct the OA. However, the method results in prominent OA removal only for single channel EEG data. Zhao *et al.* [5] proposed an online hybrid method based on DWT. The DWT coefficients were used as a reference channel for adaptive noise cancellation (ANC). Peng *et al* [13] also proposed a hybrid method, combination of DWT and ANC, to remove the eyeblink artifact from the corrupted EEG signal. Their algorithm resulted in great execution with trading off of the computation time that required as the quantity of samples increased. Noureddin *et al.* [14] used adaptive filters integrated with a high-speed eye tracker to correct the artifacts for online applications. However, to filter the data adaptively, the selection of appropriate parameters requires a complicated approach due to processing of the tracker.

Mahajan *et al.* [15] proposed an unsupervised method for eyeblink correction in EEG signals using a hybrid method of ICA and DWT. The DWT coefficients of the identified corrupted ICs were thresholded using universal threshold value to eliminate the eyeblink. Islam *et al.* [16] also used universal threshold value for correcting the eyeblink from SWT coefficients. Sai *et al.* [17] proposed an algorithm which automatically identifies the contaminated EEG signal and removes the ocular artifacts by using ICA and DWT. In their work, the wavelet coefficients of the identified corrupted IC were also thresholded using universal threshold value to eliminate the eyeblink from EEG signals. Shahbakhti *et al.* [18] used difference of absolute skewness between N^{th} and $(N-1)^{th}$ level of SWT coefficients to estimate the eyeblink artifact. If the difference is greater than an arbitrarily chosen threshold value, then the inverse SWT of that N^{th} level of SWT coefficients are considered as eyeblink and it is eliminated from the original time domain EEG signal.

Issa *et al.* [19] reported the improved eyeblink removal method using wavelet enhanced ICA technique. In their method, 1Sec. segment of corrupted ICs, where the eyeblink is present, were decomposed using DWT up to 5^{th} level. Then the low frequency components of the DWT coefficients were removed to reconstruct the clean ICs. Finally, all the clean ICs were used in the inverse ICA to get the artifact free EEG signals. More recently, Behera *et al.* [20] proposed a window based thresholding of DWT coefficients for removal of eyeblink artifacts using statistical threshold.

Unlike the conventional neural networks [21], Sanam *et al.* [22] detected the eye state through deep belief network and stacked autoencoder. This method was based on the newly developed deep learning technique and with the help of which significant accuracy was achieved. Chavez *et al.* [23] proposed surrogate based wavelet denoising technique to remove the EEG artifacts from single channel EEG signal.

From the literature survey it can be concluded that ICA, wavelet transform and adaptive filtering based methods have been used significantly in removing artifacts from EEG. ICA can be applied using the assumptions that the number of source signals should be greater than or equal to the number of independent components [17]. Hence, ICA may not be appropriate for removing artifacts from single channel EEG data. Adaptive filtering based methods require an extra reference channel which sometimes may not be available for portable applications [24]. Wavelet based methods eliminate the artifacts while retaining that highly correlated to the true EEG, but the selection of appropriate threshold is a challenging task. In the literature, universal threshold [3] and statistical threshold [3] value calculation was adopted. Both the techniques are data dependent. Hence, some tuning of the parameters for threshold calculation is required which disable the automatic correction of eyeblink artifact from the EEG signals. The effect of both the threshold calculation on the reconstruction of the original signal is discussed in this paper. Automatic selection of appropriate threshold values is a research gap for wavelet thresholding based eyeblink correction in EEG signals. Also, the quality of reconstructed EEG signal gets effected with the selection of improper wavelet function and decomposition level.

Thresholding technique is efficient in terms of implementation and the processing time for removal of artifacts. However, the automatic calculation of optimum threshold value has remained a challenging task in the removal of artifacts from EEG.

In view of the above, the main objectives of the work reported in this paper are:

i. Identification of eyeblink artifacts present in EEG signals automatically using SVM as a classifier.
ii. Selection of the optimum threshold for approximation coefficients at different levels using meta-heuristic algorithm to be implemented in a backward fashion for automatic removal of eyeblinks from EEG signal.
iii. Removing the eyeblinks from the identified contaminated EEG using the optimum threshold values for the approximation coefficients in backward fashion and applying IDWT.

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In the proposed work, the contaminated EEG is identified by the SVM classifier that is trained with some appropriate statistical features obtained from various clean EEG as well as eyeblink contaminated EEG signals for achieving significant classification accuracy. As ACs contain low frequency components, thresholding is executed on ACs. A meta-heuristic algorithm is used for optimization of the threshold value for ACs at different levels of the wavelet coefficients. A new thresholding technique is proposed here for the first time. This way of combining SVM as a classifier and selection of optimum threshold values for ACs using meta-heuristic algorithm and the backward thresholding is the maiden application in removal of artifacts from EEG signals.

The organization of the paper is as follows: Section 1 introduces the background and literature survey, section 2 describes the notations used in this paper, section 3 portrays the strategies and ideas utilized in the proposed work, section 4 elaborates the proposed algorithm, section 5 evaluates the outcome, and section 6 concludes the paper with comments made alongside the works that could be studied out later on.

II. Notations And Preliminaries

Notations	Details
$\boldsymbol{\Psi(t)}$	Mother Wavelet Function
$\boldsymbol{wt}$	Wavelet Coefficients
$\boldsymbol{A_j}$	Approximation Coefficients at level j
$\boldsymbol{D_j}$	Detail Coefficients at level j
$\boldsymbol{p_i}$	Energy probability distribution of *wt(i)*
ESER	Energy to Shannon Entropy Ratio
$\boldsymbol{R_j}$	Peak-to-sum Ratio at level j
Y	The original artifact free EEG signal
X	The eyeblink corrupted EEG signal
$\boldsymbol{Y^*}$	The reconstructed artifact free EEG signal
$\boldsymbol{\mu_Y}$	Sample mean of the signal Y
$\boldsymbol{\sigma_Y}$	Standard deviation of the signal Y
$\boldsymbol{\sigma_{YY^*}}$	Cross-correlation between Y and Y^*
$\boldsymbol{C(X,Y)}$	Covariance between X and Y
E(x)	Expectation
C-EEG	Contaminated EEG
NC-EEG	Non-contaminated EEG
$\boldsymbol{thr^l}$	Threshold value for level *l*
$\boldsymbol{Thr_{pos}}$	Threshold for positive AC at level *l*
$\boldsymbol{Thr_{neg}}$	Threshold for negative AC at level *l*
$\boldsymbol{W^{-1}}$	IDWT
$\boldsymbol{T_{hard}()}$	Hard thresholding function
$\boldsymbol{\mu_4}$	Fourth central moment

III. Materials And Methods

A. SVM Classifier

The SVM utilizes the strategy of supervised machine learning. It can competently categorize non-linear data with the kernel trick. The SVM uses training data to create optimal hyper-plane, with the aim to classify test data [27]. Some unique features of different datasets are obtained and provided to the classifier. The optimal hyperplane, known as support vectors, is made to get a decision boundary from the adjacent sample of different datasets. If the datasets are not linearly separable in the original finite dimension then the data can be re-mapped into sufficiently higher dimensional space. Linearly inseparable datasets are remapped into sufficiently higher dimensions than the original dimensions according to the kernel trick for better classification. For a thorough explanation the readers may refer to [28, 29].

B. Discrete Wavelet Transform

The EEG signal is non-stationary in nature. The wavelet transform is one of the most suitable methods to analyze non-stationary signals. Its competency in converting a time-domain signal into time-frequency localization provides advantages to realize every details of a signal better. The DWT developed by Mallat [30] is more efficient in time-frequency localization. The DWT means, picking the subsets of the scale 'j' and the time shift 'k' of the base wavelet i.e. mother wavelet $\Psi(t)$:

$$\Psi_{jk}(t) = 2^{\frac{j}{2}}\Psi(2^j\mathrm{t} - \mathrm{k}) \tag{1}$$

As the coefficients are preserved, the original input or any level decomposition can be reconstructed using inverse operation.

C. Grey Wolf Optimizer (GWO)

A simple and very recent meta-heuristic algorithm proposed by Mirjalili *et al* [31] in 2014 is Grey Wolf Optimizer (GWO). It is a swarm based intelligent method which mimics the leadership hierarchy of grey wolves when they go for group hunting. They have a very strict social hierarchy. Wolves are classified as four types: alpha, beta, delta and omega based on the nature of their behavior, with alpha the fittest individual, followed by beta, delta and omega. The stages of the grey wolf hunting are as follows:

- Following, chasing and approaching the prey.
- Tracking, surrounding and irritating the prey
- Attacking the prey

For details the readers may refer to [31].

D. Wavelet Base Selection

The selection of wavelet base function (mother wavelet) acts as the key element in signal analysis using wavelet transform. Several wavelet functions are developed over the past decade. A natural question arises on the selection of proper base: which is the best suited for analyzing a signal? Each wavelet function affects the result of wavelet transform. Since trial and error procedure is time consuming, Energy and Shannon entropy based technique is adopted for the proposed work [32]. The mathematical expression is stated as follows:

The energy and entropy of *wt* for particular scale is expressed as:

$$Energy(s) = \sum_{i=1}^{N} \parallel wt(i) \parallel^2 \tag{2}$$

$$Entropy(s) = -\sum_{i=1}^{N} p_i \times \log_2 p_i \tag{3}$$

where N is the length of wavelet coefficients.

And p_i is defined as:

$$p_i = \frac{\parallel wt(i) \parallel^2}{Energy(s)} \tag{4}$$

$$\sum_{i=1}^{N} p_i = 1 \tag{5}$$

$$p_i \times \log_2 p_i = 0 \qquad if\ p_i = 0 \tag{6}$$

The energy-to-Shannon entropy ratio (ESER) is:

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$$ESER(s) = \frac{Energy(s)}{Entropy(s)} \quad (7)$$

The wavelet function that yields the maximum value of the above stated ratio should be selected as the appropriate wavelet function for a particular signal.

E. Decomposition level selection

Selection of the decomposition level is another challenging task in wavelet analysis. Usually levels between 2 to 5 are arbitrarily selected. Selection of lower level results in poor noise cancellation and higher level results in high computational complexity. A proper level selection method is proposed in this section. The value of peak-to-sum ratio (R_j) of ACs (A_j) can help to select the decomposition level.

$$R_j = \frac{\max(\| A_j \|)}{\sum_{i=1}^{N_j} \| A_{j,i} \|} \quad (8)$$

Where, N is the length of A_j in respect to j^{th} level. The maximum level j is selected when the artifact is indistinguishable from the ACs. It is observed from the trials that the artifact is indistinguishable from the coefficients when $R_j > 0.08$. Hence, the maximum level is selected for which $R_j > 0.08$.

F. Performance Matrices

The proposed method is evaluated using the following performance measures to compare with existing artifact removal methods [17], [18], [19] and [26]. Three measures as given below are used to measure the performance

1) Normalized Mean Square Error (NMSE)

The NMSE is the most widely used tool to measure the performance of EEG signal processing [26]. The NMSE is the average squared of normalized error. It is defined as:

$$NMSE = \frac{\| Y - Y^* \|_2^2}{\| Y \|_2^2} \quad (9)$$

Generally lower NMSE value suggests good performance in artifact removal.

2) Structure Similarity (SSIM)

The SSIM measures the similarity between two signals [26]. The SSIM for Y and its reconstruction Y^* is represented as:

$$SSIM = \left(\frac{2\mu_Y\mu_{Y^*}}{\mu_Y^2 + \mu_{Y^*}^2}\right) \times \left(\frac{2\sigma_Y\sigma_{Y^*}}{\sigma_Y^2 + \sigma_{Y^*}^2}\right) \times \left(\frac{\sigma_{YY^*}}{\sigma_Y\sigma_{Y^*}}\right) \quad (10)$$

SSIM is limited from -1 to 1. SSIM = 1 can be achieved when Y=Y^*.

3) Average Correlation Coefficient (CC)

CC measures the degree of similarity between two signals [33]. In EEG artifact removal, high CC value reflects the good performance in eyeblink removal. CC is measured as:

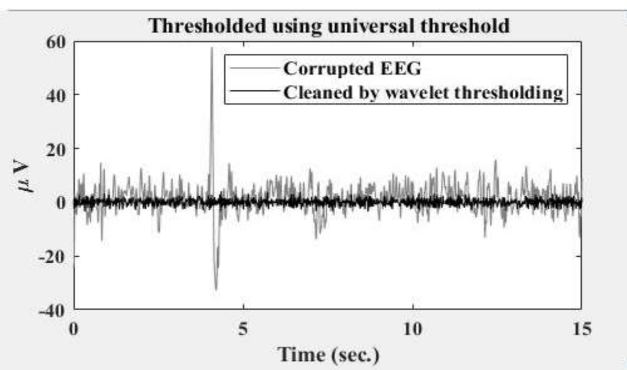
$$CC = \frac{C(Y^*, X)}{\sqrt{C(X, X) * C(Y^*, Y^*)}} \quad (11)$$

The NMSE and SSIM are used to compare the methods for simulated EEG signal. But for multi-channel real dataset, the original artifact free EEG signal is not available (there is no ground truth). Hence, average CC is used to measure the performance for real EEG dataset.

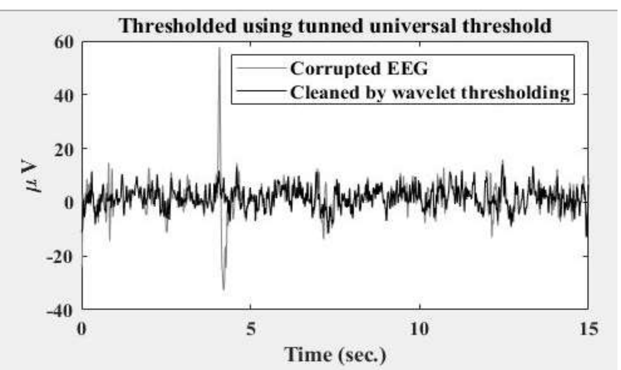
IV. Proposed Methodology

Justification of proposed thresholding approach:

The corrupted EEG signal is decomposed into wavelet coefficients and the coefficients are thresholded using universal threshold value [3] and reconstructed to get back the original EEG signal. It is evident from the figure 1(a), that the reconstructed EEG signal using universal threshold of the wavelet coefficients is distinctly different from clean EEG even though the artifact is removed. Now the calculation of threshold is upgraded through multiplication with a scalar value 5. The reconstructed signal using tuned universal threshold is shown in figure 1(b). It is evident from the figure 1(b) that, the reconstructed EEG signal using this tuned universal threshold method is better than the previous method. The wavelet coefficients are also thresholded using statistical threshold value [3] and reconstructed EEG signal is presented in the figure 2. However, the thresholding the wavelet coefficients using both universal and statistical threshold calculation function for eyeblink removal from EEG signal is not fully automatic and also results in the loss of cerebral activity. Hence, heuristically optimized threshold value selection is proposed in this work for removal of eyeblink from EEG signal.



(a)



(b)

Figure 1: The comparison between (a) the reconstructed EEG signal using universal threshold and the original EEG signal, (b) the reconstructed EEG signal using tuned universal threshold and the original EEG signal

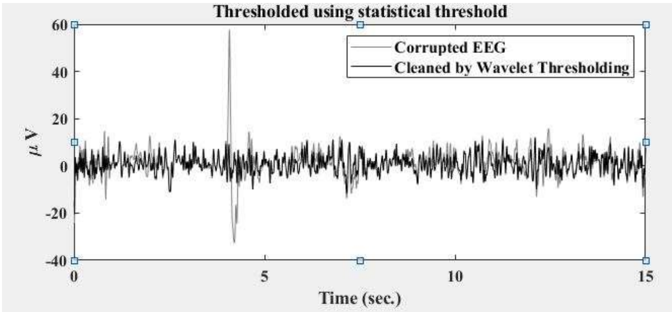


Figure 2: The reconstructed EEG signal using statistical threshold

This paper proposes a novel method for automatic identification and removal of artifact due to eyeblinks from the corrupted EEG signal. The flow chart of the proposed method is shown in figure 3. A recent meta-heuristic algorithm, GWO is used to optimize the value of thresholds for thresholding the ACs obtained from the signal with DWT in backward manner. In this method, the corrupted signal is decomposed using DWT up to level j and DCs and ACs of each level are obtained. The ACs thus obtained are thresholded. Now the thresholded ACs are used in IDWT along with DCs of level j. After IDWT at level j, new ACs at level (j-1) are found. Likewise, all the ACs at various levels are thresholded and combined successively with DCs up to level 1 to obtain the artifact free signal. Two meta-heuristic algorithms, PSO and GWO are considered for finding the optimal value of thresholds for comparative performance analysis. The proposed method is implemented in MATLAB R2019a and evaluated using simulated EEG data and validated using real-time EEG data. The proposed technique successfully erases the ocular artifact without using ICA and without any intervention by the users.

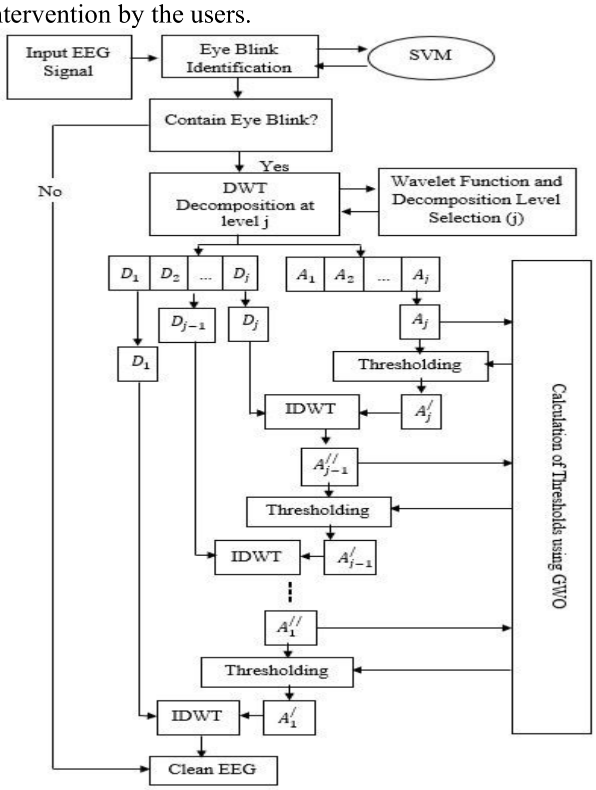


Figure 3: Block diagram of proposed method.

Stages of the proposed model:

- Three features; kurtosis, variance and peak-to-peak amplitude of the EEG signal are provided to SVM classifier as input signal,
- SVM classifies the signal as C-EEG or NC-EEG,
- C-EEG is decomposed using mother wavelet function selected by the wavelet function selection method mentioned above and up to level j. The level j is selected by calculating R_j
- ACs are thresholded in backward manner using the optimized thresholds obtained with GWO.
- Finally, the clean EEG signal is reconstructed by IDWT combining the detail and thresholded ACs at various levels till level 1.

A. Identification of Contaminated EEG

SVM classifier was trained by 100 C-EEG data and 100 NC-EEG data. For training, the data were taken from the publicly available DEAP dataset [34] with epoch size of 15 seconds. The C-EEG data were labeled as -1 and NC-EEG as 1. From the features of EEG data, the following three features were considered for identifying contaminated EEG from uncontaminated EEG.

1) Kurtosis

Kurtosis is a statistical measure that describes the degree of variation of the tails of a distribution from the tails of a normal distribution. High kurtosis value indicates heavy tails and lower kurtosis value points to light tails. The kurtosis is the fourth standardized moment defined for data Y as:

$$Kurt(Y) = E\left[\left(\frac{Y-\mu}{\sigma}\right)^4\right] = \frac{\mu_4}{\sigma^4} \quad (12)$$

2) Variance

Variance is the measure of dispersion of the data from its mean value. Variance is the average of squared difference from the mean value. The value of variance is high for contaminated EEG and less for uncontaminated EEG. Mathematically variance is expressed as:

$$Var(Y) = E[(Y-\mu)^2] \quad (13)$$

3) Peak-to-Peak Amplitude

Peak-to-Peak amplitude (pk) is a measure of the difference between maximum positive amplitude and maximum negative amplitude. It shows a high value for contaminated EEG and lower value for uncontaminated EEG signal. It is described as:

$$pk = \max(Y_i) - \min(Y_i) \quad (14)$$

In the proposed method these three features are used to identify the contaminated EEG signal. To demonstrate their effectiveness, an SVM classifier is trained using these three features of EEG signals of both types. The average value of these three features for C-EGG and NC-EEG are calculated respectively and compared in figure 4 which shows that, there is distinctive difference between corrupted EEG and clean EEG.

B. Cleaning the Contaminated EEG signals

After successful categorization of the input EEG signals, the C-EEG signal is passed on to the second phase of the proposed model for eyeblink correction. In this phase, selection of appropriate wavelet function and appropriate

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decomposition level (j) is done with proper evaluation. Further, the optimization of the set of thresholds for ACs is carried out using meta-heuristic algorithm.

1) Wavelet Function Selection

The wavelet function is selected according to the measure of ESER as mentioned above. The wavelet function with maximum ESER is selected as the mother wavelet for decomposition of the signal. The average ESER values for different EEG epochs are shown in table 1. From table 1, it is clear that the wavelet function "db8" provides the maximum energy-to-Shannon entropy ratio as compared to other wavelet functions. Hence, db8 has been selected as mother wavelet for wavelet decomposition.

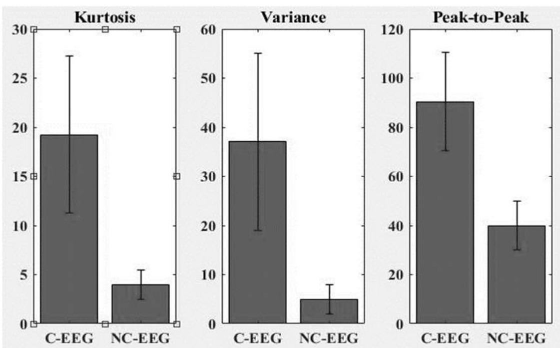

Figure 4: The average values of three discriminant features of the 100 number of C-EEG and NC-EEG data.

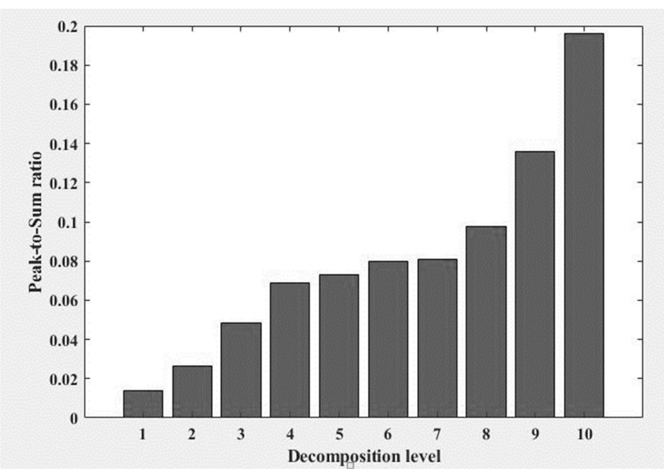

Figure 5: Peak-to-Sum ratio with respect to decomposition level. (wavelet function: 'db8')

2) Decomposition Level Selection

The decomposition level is decided according to the degree of peak-to-sum ratio (R_j). The appropriate decomposition level (j) is selected for $R_j < 0.08$. The level 6 is selected as wavelet decomposition level, because the eyeblink is indistinguishable from the coefficients when $R_j > 0.08$. The value of R_j for each level is shown in figure 5. It is observed that the value of R_j is greaterthan 0.08 after level 6, hence decomposition level for the proposed model is selected as 6.

The contaminated EEG signal is decomposed using DWT up to level 6 and db8 as wavelet function. The ACs at level 6 are extracted and divided into two arrays, namely: positive coefficients and negative coefficients.

3) Optimal Threshold Selection

Two meta-heuristic algorithms, PSO, a very frequently used algorithm by researchers for its faster convergence and GWO, for its better performance, are used for finding the optimal values of the set of thresholds for comparison of performance.

Two different set of threshold values Thr_{pos}, Thr_{neg} for positive AC and negative AC respectively are initialized randomly. Those two threshold arrays contain values according to the decomposition level. A population size of 20 is considered after experimentation with different numbers for searching the optimum threshold values. The optimized thresholds are obtained by both PSO and GWO algorithms separately for comparison. The fitness function used in the proposed work is described below.

$$THR(i) = [Thr_{pos}(i), Thr_{neg}(i)] \quad i = 1,2,\dots,l \tag{15}$$

$$Thr_{pos} = [thr^1, thr^2, \dots, thr^l] \tag{16}$$

$$Thr_{neg} = [thr^1, thr^2, \dots, thr^l] \tag{17}$$

Where l is the number of threshold required, which is the same as the decomposition level ($l = j$). As the number of levels selected are 6, hence 6 set of threshold values are required for the 6 levels. The fitness function used for the GWO and PSO is described below.

$$fitness\ function = min(RMSE/SAR) \tag{18}$$

RMSE and SAR are defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i^*)^2}{2}} \tag{19}$$

$$SAR = 10\log_{10}\frac{std(X)}{std(X - Y^*)} \tag{20}$$

Where the denoised signal $Y^*$is obtained after applying the thresholds obtained in a particular iteration for the approximation coefficients up to level l and expressed as an inverse function (W^{-1}):

Table 1: Selection of mother wavelet function.

Wavelet	Average ESER ± Std	Wavelet	Average ESER ± Std	wavelet	Average ESER ± Std	wavelet	Average ESER ± Std
Haar	6.20±2.7	**db8**	10.80 ± 1.29	**Coif3**	8.50±1.5	**Sym8**	6.14±1.5
db2	8.08±1.4	**db9**	8.26±1.01	**Coif4**	8.20±1.03	**Bior1.3**	6.88±3.9
db3	8.60±2.3	**db10**	6.57±1.2	**Coif5**	10.03±1.6	**Bior2.4**	10.14±1.71
db4	5.25±2.03	**db11**	7.85±1.3	**Sym2**	8.08±1.41	**Bior2.6**	7.40±3.47
db5	9.42±2.0	**db12**	6.32±1	**Sym3**	8.60±1.1	**Bior4.4**	6.66±1.23
db6	6.97 ± 1.03	**Coif1**	10.60±1.2	**Sym4**	9.13±1.79	**Bior5.5**	3.99±2.7
db7	7.75 ± 1.39	**Coif2**	5.60±1.8	**Sym6**	6.72±1.37	**Bior6.8**	7.93±1.58

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$$Y^* = W^{-1}(Y_{app}^l, Y_{det}^l) \tag{21}$$

The thresholded ACs Y_{app}^l are obtained with hard thresholding applied to A_l at level l and expressed as:

$$Y_{app}^l = T_{hard}(A_l, THR^l) \tag{22}$$

After finding the optimum threshold values using meta-heuristic algorithm, ACs at level l are thresholded and fed to IDWT along with l^{th} level detail coefficients to obtain the new ACs at level $l-1$. At level $l-1$, another threshold value optimized with meta-heuristic algorithm is used to threshold it and provided for IDWT operation to get a new approximation coefficient at level $l-2$. The similar process continues successively backward until level 1 is reached to obtain the artifact free signal.

V. Experimental Results and Discussion

The proposed method is tested on simulated artifactual data as well as on 32-channel recorded real EEG data. The test EEG data was given to a pre-trained SVM classifier as input to identify and classify contaminated EEG from the test EEG data base. The proposed method achieved satisfactory results in removing eyeblink components while preserving the information related to neuronal activity.

Table 2: Performance of SVM classifier

Measurements	Percentage
Accuracy	97.9
Sensitivity	98.0
Specificity	97.2

Table 3: Similarity measurement between clean EEG data and reconstructed EEG data (duration: 10 sec to 15 sec).

Methods	Average CC
Wavelet [18]	0.58
EEMD-ICA [26]	0.78
ICA-DWT [17]	0.97
ICA-DWT [19]	0.99
Proposed method	1

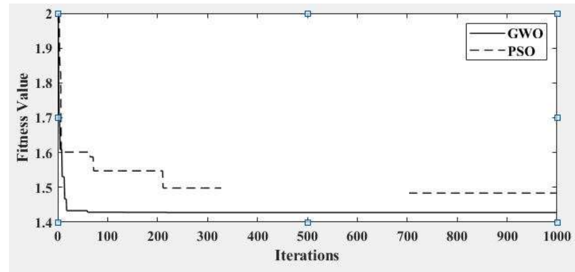

Figure 6: Convergence comparison between PSO and GWO.

A. The dataset

32-channel EEGLAB dataset [35] containing eyeblink artifacts were selected to test and validate the performance of the proposed system on real-time multi-channel EEG data. The proposed system can be applied to single channel data as well as multi-channel data for removing eyeblink artifacts.

B. Test on Single-Channel Simulated EEG Signal

An artifactual EEG signal is simulated in MATLAB for verifying the proposed model. A clean EEG signal of duration of 15 second is selected from the EEGLAB dataset based on visual inspection by an expert and an eyeblink is added to it to generate a single-channel test signal. Eyeblinks are modeled using random noise bandpass (FIR) filter between 0.1 and 3 Hz [26]. The signal is passed through the pre-trained SVM classifier. The classifier automatically identifies the corrupted signal as a C-EEG. The performance of the SVM is shown in table 2.

After detection of the C-EEG signal it is decomposed up to level 6 using DWT and 'db8' as mother wavelet function as discussed above. For the selection of optimum threshold, both the methods: GWO and PSO are implemented in the proposed method for comparison.

The performance comparison in respect of faster convergence and minimum fitness value is shown in figure 6. It can be noted that the GWO converges faster than PSO and achieves better quality solution with the minimum fitness value as compared to PSO.

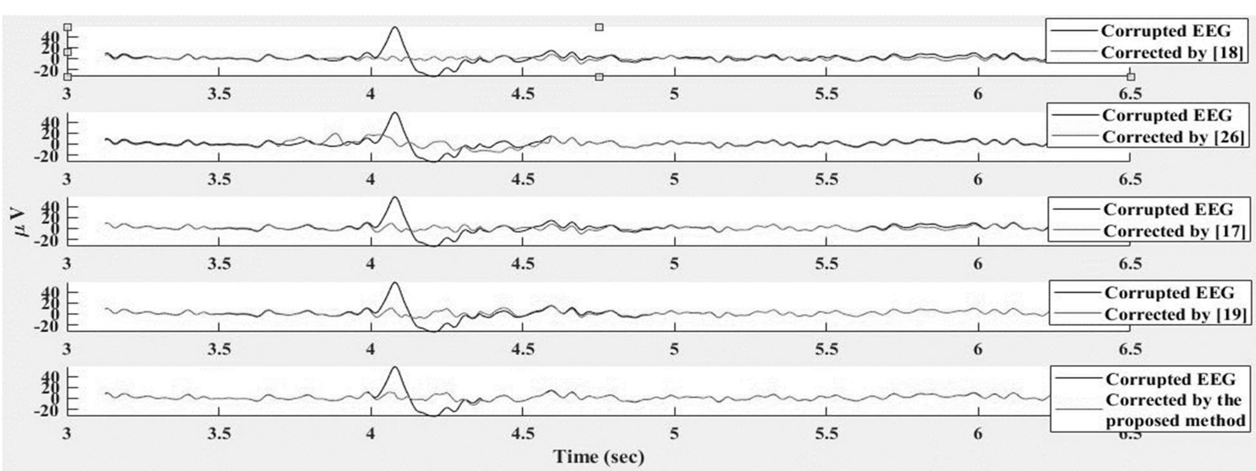

Figure 7: Comparison of simulated contaminated EEG signal and reconstructed corresponding EEG signal using the proposed method, EEMD-ICA and ICA-wavelet based method.

Table 4: Performance Comparison

Methods	SSIM	NMSE
Wavelet [18]	0.5956	0.4281
EEMD-ICA [26]	0.7750	0.1973
ICA-DWT [17]	0.8879	0.0534
ICA-DWT [19]	0.9102	0.0298
Proposed method	0.9976	0.0034

The proposed system is compared with recently developed hybrid methods described in [17], [18], [19], [26]. All the corrected EEG signals corresponding to the simulated EEG signal using these four methods and the proposed method in this paper are compared in figure 7. It is evident from the figure that the reconstructed signal with the proposed method is more accurate as compared to that of the other recently reported techniques. Hence, it demonstrates that the proposed method can automatically remove the artifact and also preserve the true EEG structure more accurately and efficiently.

The corrected EEG signals obtained after reconstruction with all the five methods are compared with their true clean EEG signal in figure 8. Figure 8(a) shows the comparison between true artifact-free EEG and the corrected EEG signal reconstructed by [18]. It is observed that the reconstructed signal with this method exhibits higher variation to the clean EEG signal . The EEG signal reconstructed with the method [26] is slightly better than the method [18] as shown in figure 8(b). It is evident from figure 8(c) and 8(d) that the method [17] and [19] reconstruct the signal more closely to the

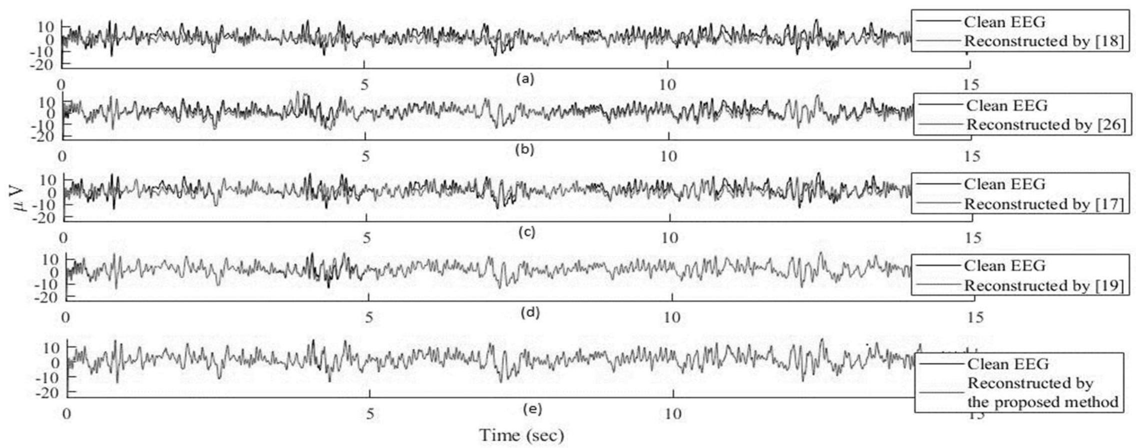

Figure 8: Comparison of true clean EEG signal and clean signal reconstructed by all three methods.

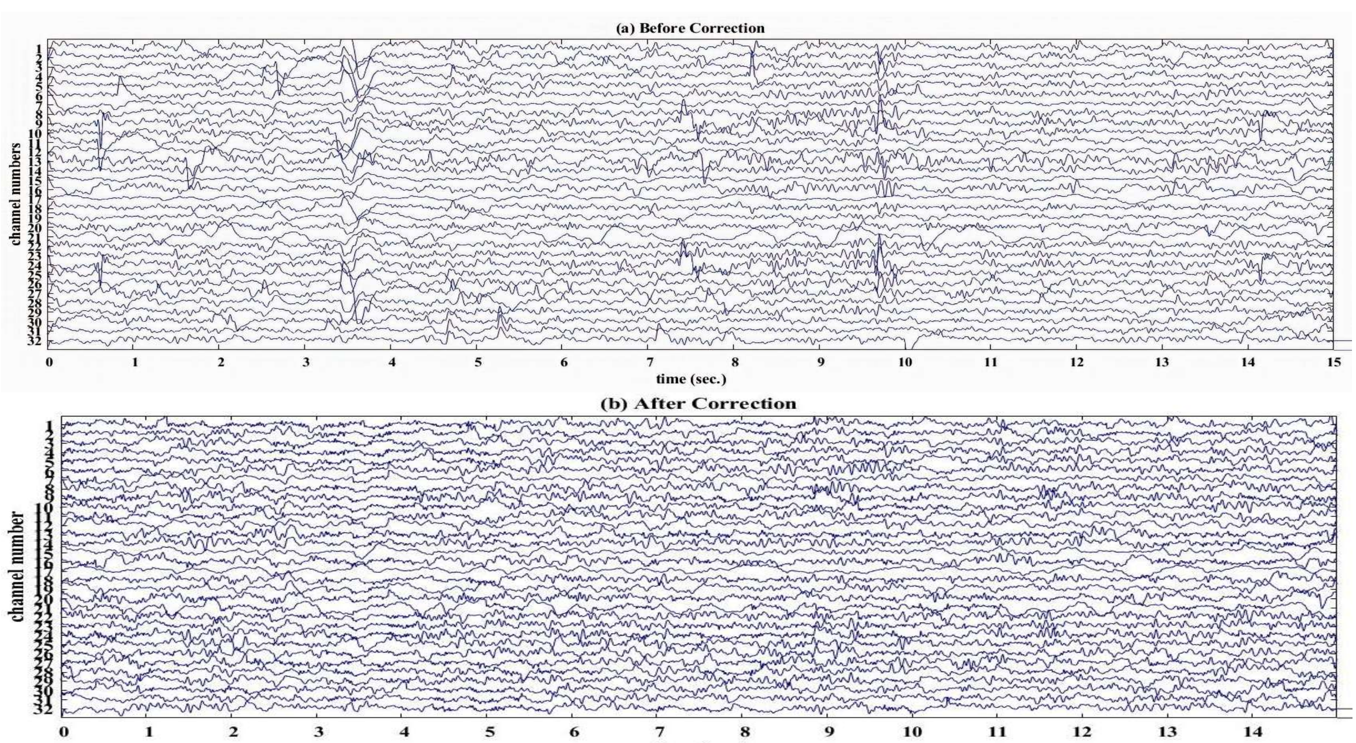

Figure 9: 32-channel recoded data: before correction and after correction, (a) the 15 second artifacted raw EEGLab dataset, (b) the clean EEG signal reconstructed by the proposed method.

original EEG signal. The EEG signal corrected and reconstructed by the proposed method is shown in figure 8(e). To check the superiority of the proposed method on reconstruction, the average CC between clean EEG signal and reconstructed EEG signal ranging from 10 sec. to 15 sec. is calculated and presented in table 3. It is evident that the proposed system corrects the eyeblink much better than other methods while maintaining the true EEG nature in other parts of the signal. Hence, to correct the corrupted EEG signal by the proposed method, the loss of information is very less.

Further, for quantification and measurement of performance of the methods two statistical performance measures, NMSE and SSIM are calculated for all the methods and shown in table 4. Lower NMSE value reflects that the signal is reconstructed more accurately. Higher SSIM value reflects that the artifact free reconstructed EEG signal has better structural similarity with the original clean signal. It can be observed that the SSIM is higher and NMSE is lower for the proposed method as compared to the other methods. Hence, it can be said that as verified and validated the proposed model has been more competent to remove artifact from corrupted EEG signals.

C. Test On Recorded Multi-Channel Real EEG data

In this section the proposed system is tested using the publicly available EEG dataset mentioned above (EEGLAB dataset). The 32 channel raw data were selected and bandpass filtered between 1 to 40 Hz. Eyeblink contaminated 15s of filtered EEG data were taken for evaluation. However, all channels are partially affected by eyeblink and are shown in figure 9(a). The proposed method automatically identifies all the contaminated EEG and cleans all the eyeblink artifacts present in every channel data. The 32-channel artifact free reconstructed EEG signal is presented in figure 9(b). The average CC between artifacted EEG signal and corresponding reconstructed clean EEG signal is measured to test the performance in reconstruction of the original signal. Table 5 shows the performance of the proposed method as well as four other denoising methods reported earlier. It can be observed that the proposed method achieved higher correlation with the true EEG signal as compared to the recently developed methods.

VI. Conclusions And Future Scope

In this work an innovative idea of thresholding the ACs of EEG signals instead of detail coefficients in backward manner is proposed for the first time for efficient elimination of eyeblink artifacts from corrupted EEG data. Further, the threshold values are optimized using modern meta-heuristic algorithm. The proposed method is fully automatic and once trained does not require any intervention of the user while using it. SVM is used as the classifier to recognize whether EEG signal is corrupted with artifact or not. DWT is used for decomposing the artifacted EEG signal into time-frequency space. It performs well in handling non-stationary data while preserving true signal structure. Wavelet function is also selected using an appropriate way. And the decomposition level was selected by calculating the peak-to-sum ratio. Two algorithms, PSO and GWO were used to find the optimal set of values for thresholding different ACs at different levels for comparison and GWO is found to give better performance in terms of convergence and quality of solution. Hence, GWO is used in this proposed approach for selection of optimal values for thresholding ACs at different levels. These optimal set of threshold values are used to find the thresholded ACs at different levels in IDWT in backward fashion to find the corrected EEG signal. The proposed method is first validated with simulated EEG data which demonstrates better performance and then tested with publicly available real time recorded EEG data for practical validation. The proposed method can be implemented in online mode and for multi-channels. Future studies are likely to investigate the performance of the proposed method in removing other kinds of artifacts.

Table 5: Comparison of Average Correlation Coefficients

Channel	Average Correlation Coefficients				
	Wavelet [18]	**EEMD-ICA [26]**	**ICA-DWT [17]**	**ICA-DWT [19]**	**Proposed method**
Channel 1	0.3418	0.4235	0.4614	0.4754	**0.5642**
Channel 2	0.6076	0.7153	0.7521	0.7914	**0.8098**
Channel 3	0.4561	0.5473	0.5986	0.6105	**0.6493**
Channel 4	0.4476	0.4929	0.5275	0.5835	**0.6269**
Channel 5	0.5203	0.5907	0.6244	0.6830	**0.6987**
Channel 6	0.6269	0.6891	0.7015	0.7304	**0.7725**
Channel 7	0.5264	0.6296	0.6659	0.6795	**0.8490**
Channel 8	0.6409	0.7355	0.7355	0.7451	**0.7884**
Channel 9	0.4784	0.5872	0.6117	0.6230	**0.6337**
Channel 10	0.4123	0.4967	0.5206	0.5320	**0.6242**
Channel 11	0.4692	0.5604	0.5892	0.6141	**0.7403**
Channel 12	0.5507	0.6708	0.7184	0.8063	**0.9524**
Channel 13	0.4874	0.5744	0.6018	0.6071	**0.6411**
Channel 14	0.5908	0.6878	0.7229	0.7493	**0.7572**
Channel 15	**1**	**1**	**1**	**1**	**1**
Channel 16	0.5958	0.7229	0.7382	0.7651	0.7784
Channel 17	**1**	**1**	**1**	**1**	**1**
Channel 18	0.6297	0.7217	0.7804	0.7559	**0.7945**
Channel 19	0.5713	0.6585	0.6893	0.7298	**0.9288**
Channel 20	0.6411	0.7366	0.7366	0.7892	**0.8486**
Channel 21	0.2845	0.3899	0.4235	0.4647	**0.7613**
Channel 22	0.6541	0.7118	0.7203	0.7666	**0.7941**
Channel 23	0.6175	0.7417	0.7417	0.7454	**0.8195**
Channel 24	0.5284	0.6049	0.6171	0.6106	**0.6283**
Channel 25	0.6940	0.8474	0.8756	0.8899	**0.9121**
Channel 26	0.5857	0.6810	0.7340	0.7382	**0.7409**
Channel 27	0.3975	0.4744	0.4967	0.5080	**0.5280**
Channel 28	0.5181	0.6291	0.6738	0.6915	**0.7457**
Channel 29	0.5650	0.6446	0.6762	0.7671	**0.7696**
Channel 30	0.5444	0.6366	0.7113	0.7191	**0.7568**
Channel 31	0.6067	0.6922	0.7186	0.8110	**0.8392**
Channel 32	0.5593	0.6808	0.7286	0.7471	**0.7644**
Average ± std	0.5672 ± 0.14	0.6555 ± 0.13	0.6842 ± 0.12	0.7103 ± 0.12	**0.7662 ± 0.11**

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