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PAPER

# Improvements of EEG Signal Quality: A Hybrid Method of Blind Source Separation and Variational Mode Destruction to Reduce Artifacts

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**ABSTRACT**

The electroencephalogram (EEG) is a crucial tool for studying brain activity; yet it frequently encounters artifacts that distort meaningful neural signals. This paper addresses the challenge of artifact removal through a unique hybrid method, combining Variational Mode Decomposition (VMD) techniques with Blind Source Separation (BSS) algorithms. VMD, recognized for its adaptability to non-linear and non-stationary EEG data, as well as its ability to alleviate mode mixing and the "endpoint effect," which serves as an effective preprocessing step. The paper evaluates the performance of two integrated BSS algorithms, AMICA and AMUSE, across various criteria. Comparisons across metrics such as Euclidean distance, Spearman correlation coefficient, and Root Mean Square Error reveal similar performance between AMICA and AMUSE. However, a distinct divergence is evident in the Signal to Artifact Ratio (SAR). When employed with VMD, AMICA demonstrates superiority in effectively discerning and segregating brain signals from artifacts, which gives a mean value of 1.0924. This study introduces a potent hybrid VMD-BSS approach for enhancing EEG signal quality. The findings emphasize the notable impact of AMICA, particularly in achieving optimal results in artifact removal, as indicated by its superior performance in SAR. The abstract concludes by underlining the significance of these results, emphasizing AMICA's pivotal role in achieving the highest measurable evaluation value, making it a compelling choice for researchers and practitioners in EEG signal processing.

**KEYWORDS**

blind source separation, variational mode decomposition, electroencephalogram, artifact

## 1 INTRODUCTION

The electroencephalogram (EEG) is a representation of the combined electrical activity originating from the functioning human brain [1, 2]. The cerebral cortex comprises approximately 10^9 to 10^10 neurons, and the amalgamated electrical field of

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this cortex can be measured using scalp-affixed electrodes and an appropriate amplification system. These electrodes are positioned in standardized locations across key anatomical regions, including the frontal, temporal, and parietal lobes. Notably, the electrical phenomena on the scalp are intermittently sampled, rendering the EEG signal not a direct measure of individual neuron behaviour but rather reflective of synchronized activity among neuron populations. The EEG signal is analysed in the frequency domain, with distinct frequency ranges corresponding to different mental states and cognitive processes [3]. The EEG signal is susceptible to artifacts, which are signals not originating from the brain but rather caused by external sources. These artifacts can arise from physiological or non-physiological factors, impacting data fidelity. Physiological artifacts encompass internal sources like ocular, muscle, cardiac, perspiration, and respiration activities, while non-physiological artifacts stem from external origins, including instrumental factors, interference, and movement-related issues involving electrodes, cables, sound, and electromagnetic forces. During EEG data collection using recording systems, these artifacts gain prominence and can potentially compromise data integrity [4–6]. Hence, a wide range of tools created for artifact rejection has been developed, serving the needs of researchers and medical professionals.

As a result, both academics and medical physicians have access to a variety of instruments made specifically to reject artifacts. The initial category of tools revolves around single-channel decomposition, a process accomplished through a sequence of three stages: decomposition, artifact elimination, and reconstruction. The decomposition phase involves several methodologies, including Variational Mode Decomposition (VMD), which dissects a signal into its constituents, alongside wavelet, Fourier series decomposition, and Empirical Mode Decomposition (EMD) [7]. This methodology also facilitates the extraction of artifacts from individual EEG data channels [8]. The subsequent category employs Blind Source Separation (BSS), a widely acclaimed approach for eradicating artifacts from EEG signals [9]. BSS, an unsupervised learning technique, takes the recorded signals as input and endeavours to infer the source signals, encompassing both original signals and artifacts [5, 6]. Diverging from the first set of techniques, this strategy eliminates artifacts across numerous EEG channels. In addition, there exists another classification of methods referred to as hybrid approaches, where two or more techniques are merged to enhance artifact removal [8]. The key limitation of these methods is their potential to impact fundamental neural functioning. This stems from the fact that the elements subject to subtraction or elimination during the decomposition step could encompass crucial neural information. To address this concern, multiple research studies have been introduced. Each of these studies strives to enhance the artifact-rejection process by homing in on minimizing the loss of essential cerebral activity that might otherwise be removed [10, 11].

In the ever-evolving landscape of EEG signal processing, numerous methodologies have been proposed to enhance the extraction of meaningful neural information while mitigating the impact of artifacts. Among these pioneering contributions, Klados et al. introduced the REG-ICA algorithm [10]. This algorithm employs a regression scheme to filter the independent components generated through BSS techniques. Stergiadis et al. [12] embarked on an exploration of the mathematical and statistical effectiveness of five widely utilized BSS algorithms. Their assessment employed metrics like the Spearman correlation coefficient, Shannon entropy, and Euclidean distance to gauge the efficacy of these methods. In the context of artifact removal, Jamil et al. [11] amalgamated Discrete Wavelet Transform (DWT) with Independent Component Analysis (ICA). Tong et al. [13] directed their efforts toward mitigating artifacts and interference within EEG recordings. They employed ICA to disentangle brain and heart activity signals, specifically focusing on small animals. Their strategy hinged on the statistical independence of these signals, particularly addressing challenges posed by cardiac pulse interference. A novel adaptive filtering technique is proposed by P. He et al. [14] for the proficient removal of electrooculogram (EOG) artifacts from frontal-channel EEG signals. This approach leverages separately recorded vertical and horizontal EOG signals as references, which are filtered through finite impulse response filters and then subtracted from the original EEG. Executed via a recursive least-squares algorithm with a forgetting factor, the method demonstrates stability, rapid convergence, and suitability for online EOG artifact removal, substantiated by experimental data. Addressing the formidable task of artifact removal, Kiamini et al. [15] target Ocular Artifacts, significantly stronger than EEG signals due to eye blinks and movements. Their innovative approach automatically identifies OA regions in contaminated EEG signals, subsequently employing stationary wavelet transform (SWT) to eliminate them. The technique reconstructs artifact-free EEG signals by capitalizing on correlation coefficients between wavelet coefficients of OA regions in the contaminated EEG and corresponding regions in the electrooculogram (EOG). To tackle EEG activity analysis challenges, Turnip et al. [16] introduce a multi-pronged method. This involves wavelet denoising and bandpass filtering for preprocessing, alongside a robust principal component analysis algorithm for artifact removal. Adaptively generating decor-related linear combinations of variables retains essential information while effectively eradicating artifacts in real EEG records from eight subjects. Paulraj et al. [17] strive to augment the quality of Electroencephalogram (EEG) signals compromised by diverse artifacts. Their method entails feature extraction (fractal dimension and time-domain energy) and utilization of neural network models to differentiate between normal and noisy EEG signals, achieving an impressive peak classification accuracy of 95.5%. Mowla et al. [18] present a targeted hybrid methodology, commencing with the fusion of Canonical Correlation Analysis (CCA) and SWT for EMG artifact mitigation. Subsequently, they incorporate the SOBI algorithm (a BSS technique) in conjunction with SWT for efficient EOG artifact eradication. In their study, Dora et al. [19] presented an algorithm aimed at rectifying ECG artifacts in single-channel EEG signals. Their approach utilized a customized version of variational mode decomposition (mVMD). They evaluated their method against two existing techniques using a semi-simulated dataset, with the goal of improving automated analysis and diagnosis of compromised single-channel EEG signals. Another innovative strategy, proposed by Liu et al. [20] combined Variational Mode Decomposition (VMD) and Second-Order Blind Identification (SOBI) to eliminate artifacts from single-channel EEG signals. They validated their approach on synthetic signals containing both genuine EEG and artifact components. Applying their VMD-SOBI approach to real EEG data, they compared its performance against existing techniques, optimized key VMD parameters, and concluded with a summary of findings and future research prospects in the field.

In light of this, this work suggests a novel hybrid technique to enhance the removal of ocular aberrations from the EEG data. Ocular artifacts pose a significant challenge in EEG recordings, introducing unwanted signal variations due to eye-related movements such as blinks and saccades. These artifacts can substantially distort the neural signals of interest, necessitating their careful identification and removal for accurate analysis. The VMD and the BSS, two well-known techniques, serve as the foundation of our strategy. Here, we suggest utilizing VMD to perform an initial decomposition of each EEG signal into its IMFs. These functions will then be used as input for the BSS algorithms, further decomposing them into separate components and rejecting artifacts. By integrating two distinct signal decomposition methods, the goal of this approach is to clean the EEG without altering the underlying neural information. The Euclidean distance and Spearman correlation coefficient were used to assess our technique and compare the effectiveness of the algorithms applied.

Following is the breakdown of the rest text in the article. The data and techniques used in our investigation are explained in Section 2, along with the VMD strategy and the BSS algorithms that were employed in our work. According to the aforementioned assessment aspects, Section 3 shows the results for the performance of the five hybrid algorithms, and Section 4 concludes our work by discussing our findings in light of the literature at large.

## 2 MATERIALS AND METHODS

### 2.1 Datasets

In the present study, we used an open semi-simulated EEG/EOG dataset that was generated to test the artifact removal techniques. This dataset may be found at https://github.com/ramsys28/BSSCompPaper. This dataset comprises EEG recordings obtained from 27 individuals in good health. These participants engaged in a session where their eyes were closed. The group consisted of 14 men (an average age of 28.2 ± 7.5 years) and 13 women (an average age of 27.1 ± 5.2 years). For each individual, two recordings were taken, resulting in a total of 54 recordings. Each recording lasted for a duration of 30 seconds.

In accordance with the 10–20 international system, 19 EEG electrodes were positioned on the scalp, specifically FP1, FP2, F3, F4, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, Fz, Cz, and Pz. The connected earlobe montage was utilized to record the signals. To ensure data quality, the samples underwent notch filtering at 50 Hz after an initial bandpass filtering in the range of 0.5 to 40 Hz. The sampling rate for the recordings was 200 Hz.

The EOG signals from the identical participants were recorded when their eyes were open. This was done by placing two electrodes on the outer corners of each eye and two electrodes above and below the left eye. This approach resulted in the generation of two bipolar signals: the horizontal-EOG (*HEOG*), which is derived from the difference between the left and right EOG electrode recordings, and the vertical-EOG (*VEOG*), which is calculated by subtracting the lower EOG recording from the upper EOG recording. To enhance the quality of these EOG signals, a band-pass filter ranging from 0.5 to 5 Hz was applied during the preprocessing stage.

The semi-simulated dataset used in our work is constructed using the following model:

$$EEG_X = EEG_S + d \times HEOG + c \times VEOG \tag{1}$$

$EEG_S$ refers to the signals recorded during the closed-eye session, while $EEG_X$ represents the intentionally contaminated EEG data. The contamination coefficients for previously described *VEOG* and *HEOG* signals are determined by the vectors $d$ and $c$ [21].

### 2.2 Variational mode decomposition

The Variational Mode Decomposition (VMD), introduced by Dragomiretskiy and Zosso in 2014, presents a distinctive non-recursive signal processing technique for signal decomposition into intrinsic mode functions (IMFs), where each IMF is conceptualized as a bandwidth-limited amplitude-modulated frequency-modulated (AM-FM) signal. This method entails iteratively determining the optimal solution of a constrained variational model, which facilitates the adjustment of frequency centres and bandwidths for each IMF component, resulting in a highly effective decomposition. The central principle of VMD lies in representing each mode as a narrowband signal characterized by a slowly evolving envelope, setting it apart from conventional decomposition approaches [20]. The given signal $X$ is segmented into a distinct set of these modes. By solving a constrained variational problem as per theoretical specifications [22]:

$$min_{u_k, w_k} = \left\{ \sum_{k=1}^{K} \left\| \partial \left[ \left( \partial(t) + \frac{j}{\pi t} \right) * u_k \right] e^{-jw_k t} \right\|_2^2 \right\} s.t; \sum_{k=1}^{K} u_k = X(t) \tag{2}$$

In this context, $\delta(t)$ represents the Dirac distribution, and * as well as ∂ stand for the convolution and partial differential operators, respectively. The notations $u_k$ and $w_k$ correspond to the mode number $k$ (where $k = 1, 2, \ldots, K$) within the framework of VMD, along with its corresponding centre frequency. The solution is attained by pinpointing the critical point of the augmented Lagrangian $\mathcal{L}$, which can be expressed as [22, 23]:

$$\begin{aligned} \mathcal{L}(\{u_k\},\{w_k\},\lambda) = \alpha \sum_{k=1}^{K} \left\| \partial \left[ \left( \partial(t) + \frac{j}{\pi t} \right) * u_k \right] e^{-jw_k t} \right\|_2^2 + \left\| X(t) - \sum_{k=1}^{K} u_k(t) \right\|_2^2 \\ + \left\langle \lambda(t) X(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \end{aligned} \tag{3}$$

In the context where the penalty for sentencing is denoted as $\alpha$, the application of the alternate direction method of multipliers (ADMM) offers a means to ascertain the location of the saddle point for $\mathcal{L}$. The introduction of Wiener filtering in the Fourier domain promptly leads to modifications in the optimal value of $u_k$.

## 2.3 Blind source separation

Blind source separation, a statistical and signal processing technique, is employed to break down a collection of signals into their distinct components. This method finds utility in several domains including medicine, telecommunications, and other sectors [24]. BSS is a set of techniques used to separate a set of mixed signals called the observation, into their original source signals (sources) without any prior knowledge of the mixing process [25].

$$X(J, m) = A(S(Q, m)) \tag{4}$$

$A$ indicates the mixed function of the sources, $S$ represents a matrix of $J$ signals sources, and $X$ is a matrix of $Q$ observations.

We can distinguish a number of the mixed functions between the source and the observation. The simplest mixed function or model is the instantaneous linear mixture. The observations at each moment are simultaneous linear combinations of the sources. A mixing matrix $A$ with dimensions (P, N) serves as the mixing model in this case, and we can represent the mixing function as this formula:

$$X(J, m) = A \times S(Q, m) \tag{5}$$

An unmixing matrix, denoted as $B$, can be employed to disentangle the initial signals, as indicated by this equation:

$$Y(Q, m) = B \times X(J, m) \tag{6}$$

In our study, we used two BSS methods:

a) **The Adaptive Mixture Independent Component Analysis (AMICA)**

The Adaptive Mixture Independent Component Analysis (AMICA) is one of the Independent Component Analysis (ICA) tools, which is a set of techniques based on the Higher-Order Statistics (HOS) of the signals [24]. The ICA technique aims to determine estimations of unidentifiable sources by matching them to signals characterized by maximal independence. The algorithms typically comprise two main phases: first, the whitening step, followed by the enhancement of independence through the utilization of higher-order statistics [26]. The AMICA method stands as a versatile probabilistic framework for ICA, adept at accommodating non-stationary environments and arbitrary source densities. This method employs an asymptotic Newton algorithm for Quasi Maximum Likelihood estimation of the ICA mixture model, utilizing ordinary gradient and Hessian computations. Its efficacy lies in enhancing convergence, particularly when dealing with scenarios such as the multiple model case, where the feasibility of pre-whitening diminishes. At its core, AMICA harnesses a three-layer mixing network to model non-stationary data. The upper two layers encompass one or more ICA mixture models, each deciphering adaptively learned segments of the data into statistically independent sources. The second layer amalgamates these ICA models' outputs, capturing the data's inherent non-stationarity. Unique to AMICA, the third layer fine-tunes each learned model to effectively account for distinct subsets of the data, making it a powerful tool for deciphering complex and dynamically changing data distributions [27, 28].

b) **The Algorithm for Multiple Unknown Signals Extraction (AMUSE)**

The Algorithm for Multiple Unknown Signals Extraction (AMUSE) is a member of a group of algorithms based on a signal's Second Order Statistics (SOS). More specifically, this group of techniques makes use of the joint diagonalization of several time-delayed covariance matrices calculated from the observation [26]. The AMUSE algorithm is a blind identification method that can extract the channel characteristics and the source signals from observation vectors [29]. The AMUSE algorithm steps can be described as follows: The observed data $X$ is transformed linearly in the first step using a conventional or robust pre-whitening:

$$X_1 = Q \times X \tag{7}$$

Where:

$$Q = R_x^{-\frac{1}{2}} \tag{8}$$

In addition, $R_x$ is the common covariance matrix of the observed data. $X_1$ is then used to represent the pre-whitened data. The time-delayed covariance matrix of the pre-whitened data is computed in the next step as follows:

$$R_{X_1X_1} = E\{X_1(t)X_1(t-1)\} \tag{9}$$

Where $t$ indicates the time. And then, this covariance matrix is subjected to the SVD in the second phase. The SVD divides this matrix into three matrices: U, $\Sigma$, and $V^T$, where U and V are orthogonal matrices made up of left and right singular vectors, respectively, and $\Sigma$ is a diagonal matrix with decreasing singular values. In the end, $W$ is used to estimate an unmixing (separating) matrix:

$$W = U^TQ \tag{10}$$

Utilizing this matrix, the pre-whitened data $X_1$(k) is converted into the estimated source signals S(k) = W$X_1$(t), which are then employed in the analysis [25].

## 2.4 Proposed method

This research introduced an approach that merges VMD techniques and BSS methods to eliminate the ocular artifact from EEG signals. Initially, every signal underwent a process of decomposition into a matrix of Intrinsic Mode Functions (IMFs) using the VMD method (Figure 1). Subsequently, the fundamental sources were determined by employing BSS algorithms, using the previously mentioned matrix of IMFs as the input.

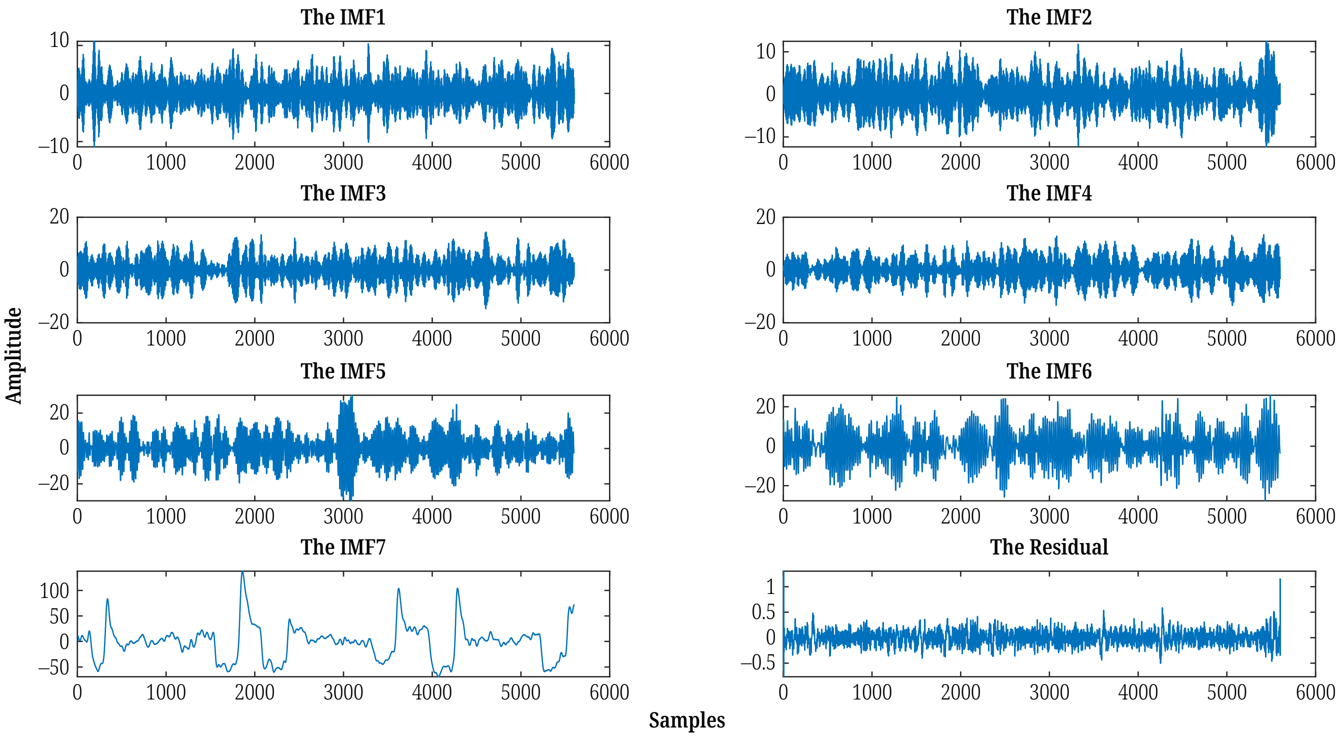


**Fig. 1.** *The IMFs (imf1, imf2, imf3, imf4, imf5, imf6, imf7) and the residual of the raw EEG signal*

The following phase involves implementing a process of hard thresholding to identify and eliminate artifacts. The specific threshold utilized in our investigation is determined by the following expression:

$$Ri = \sigma i \sqrt{2log(N_i)} \tag{11}$$

Where $$\sigma i = median\ (Si(t))/(0.67 \cdot E) \tag{12}$$

In this context, $N_i$ represents the number of samples within the ith sources $Si(t)$. The constant value $E$, which is set to 2 in this instance [6], is also involved. The method of thresholding employed in our study is elucidated by the subsequent equation:

$$TR(y) = \begin{cases} Y & if \quad Y < R \\ 0 & if \quad Y > R \end{cases} \tag{13}$$

where $TR(y)$ indicates the ith denoised source [18].

The last phase of our method involves utilizing BSS to combine the purified sources, followed by employing inverse VMD to reconstruct the initial signals.

This sequence of steps leads to an outcome where the ocular artifact is removed, resulting in a clear EEG signal. The process is illustrated in Figures 2 and 3.

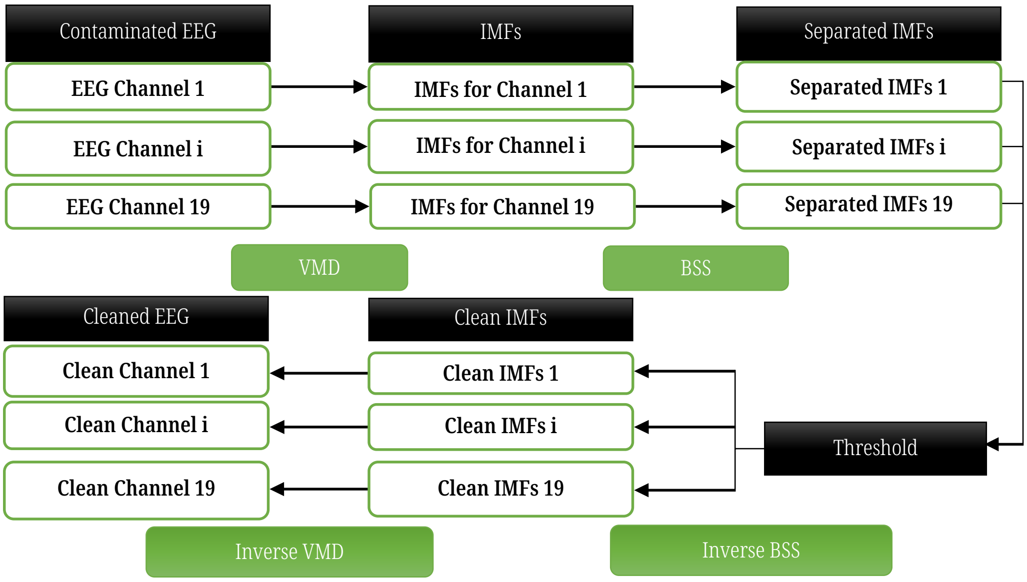


**Fig. 2.** The phases of the proposed approach (VMD-BSS). The graphic consists of five steps: 1) EEG decomposition using VMD; 2) The data is mixed using inverse BSS methods and the five BSS algorithms; the ocular artifact is eliminated using threshold. note that i indicates the channel number (from 1 to 19)

```
function EEGArtifactRemoval(rawEEGData):
  # Step 1: Apply Variational Mode Decomposition (VMD) to extract In-trinsic Mode Functions (IMFs)
  IMFs = VMD(rawEEGData)

  # Step 2: Apply Blind Source Separation (BSS) to separate IMFs
  separatedIMFs = BSS(IMFs)

  # Step 3: Apply hard thresholding to eliminate artifacts in separat-ed IMFs
  cleanIMFs = HardThresholding(separatedIMFs)

  # Step 4: Apply inverse BSS to reconstruct separated IMFs
  reconstructedIMFs = InverseBSS(cleanIMFs)

  # Step 5: Apply inverse VMD to obtain the clean EEG signal
  cleanEEGSignal = InverseVMD(reconstructedIMFs)

  return cleanEEGSignal

for i: 1 –> 19:
        EEGcln[i] = EEGArtifactRemoval (EEGx[i])
```

**Fig. 3.** A simple pseudo code for the proposed VMD-BSS method for Ocular Artifact removal algorithm. Where i indicates the number channel

## 2.5 Evaluation criteria

In the present research, we employed two features that are frequently used to assess the artifact-removing approaches in earlier work to gauge the effectiveness of our suggested method. Our metrics were derived using the difference between the initial, or $EEG_s$ signals recorded during an eyes-closed session and the cleaned

EEG signals generated using the provided methods. This process was used for each of the 54 data and for each of the developed combination algorithms. The algorithms are compared using the same criteria to select the one that performs best in the context of the proposed VMD-BSS approach.

**a) The Spearman Correlation Coefficient:**

The Spearman correlation coefficient (*C*) is a nonparametric indicator of the strength and direction of a relationship between two variables. Instead of real values, it is based on the data's rankings. The coefficient ranges from –1 to 1, where a perfect negative correlation is represented by a value of –1, a perfect positive correlation by a value of 1, and no correlation by a value of 0. When the data are not regularly distributed or when outliers are present, the Spearman correlation coefficient is frequently employed. The procedure for calculating it involves rating the data for each variable first, then calculating the Pearson correlation coefficient between the ranks [30]. This type of correlation is given by:

$$C = 1 - 6\sum \frac{d^2}{t(t^2 - 1)} \tag{14}$$

where $t$ represents the overall number of value pairings and $d$ shows the statistical difference between the two sets of compared data [30].

**b) The Euclidean Distance:**

The shortest distance between any two locations in the Cartesian coordinate system is known as the Euclidean distance (*ED*). This distance is represented by the length of the line that connects those two locations [12]. The *ED* formula used between two points is represented by [31]:

$$ED = \sqrt{\sum_i (x_i - x_i')^2} \tag{15}$$

Where $x_i$ and $x_i'$ are the coordinates of the two points. A short Euclidean distance between the produced (artifact-free) reconstructed signal and the $EEG_S$ signals obtained while keeping your eyes closed would indicate a successful artifact removal procedure.

**c) Root Mean Square Error:**

The Root Mean Square Error (RMSE) serves as a widely employed metric for assessing the fidelity of a denoised signal. This metric quantifies the average discrepancy between the original signal and its denoised counterpart, factoring in the magnitude of these disparities. A reduced RMSE value signifies an enhanced quality of the denoised signal, reflecting that, on average, the disparities between the original and denoised signals are less pronounced [30]. The RMSE is computed using:

$$rmse = \sqrt{\frac{1}{N}\sum(EEG_{cln} - EEG_s)^2} \tag{16}$$

$EEG_{cln}$ represents the corrected *EEG*. The greater the reduction in RMSE values following the application of an artifact rejection algorithm, the higher the level of optimization achieved in its performance.

**d) Signal to Artifact ratio:**

The improvement in the signal-to-artifact ratio (SAR) is determined by comparing the SAR values before and after artifact removal. This enhancement, denoted as "SAR", signifies whether the signal-to-artifact ratio has increased, decreased, or remained unchanged, thus reflecting changes in signal quality. Mathematically, the gain in the signal-to-artifact ratio (Y) is expressed as follows:

$$\Gamma = 10\log\left(\frac{SAR_A}{SAR_B}\right) \tag{17}$$

$SAR_A$ represents the signal-to-artifact ratio once artifacts have been eliminated from the EEG signal, while $SAR_B$ denotes the signal-to-artifact ratio prior to artifact removal. These ratios are computed using the following formulas:

$$SAR_A = \frac{\frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{EEG_s}\right|^2}{\frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{cln} - \mathrm{EEG_s}\right|^2} \tag{18}$$

$$SAR_B = \frac{\frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{EEG_s}\right|^2}{\frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{EEG_x} - \mathrm{EEG_s}\right|^2} \tag{19}$$

## 3 RESULTS AND DISCUSSION

In this research, our objective was to enhance the elimination of ocular disturbances from EEG signals that had been affected. We achieved this by employing a hybrid approach combining the BSS and VMD techniques (see Figures 4–7). The average values for the evaluation metrics for the two BSS algorithms across the 54 datasets are displayed in Table 1.

**Table 1.** Descriptive data are provided for the following metrics after using the two distinct VMD-BSS algorithms: Euclidean Distance (EC), Spearman Correlation Coefficient (SCC), Root Mean Square Error (RMSE), and Signal to Noise Ratio (SAR)

| | VMD – AMICA | VMD – AMUSE |
|---|---|---|
| **Spearman correlation coefficient** | 0.8068 | 0.8196 |
| **Euclidean distance** | 721.2634 | 704.3926 |
| **Root Mean Square Error** | 9.3149 | 9.0467 |
| **Signal to Artifact ratio** | 1.0924 | 0.1653 |

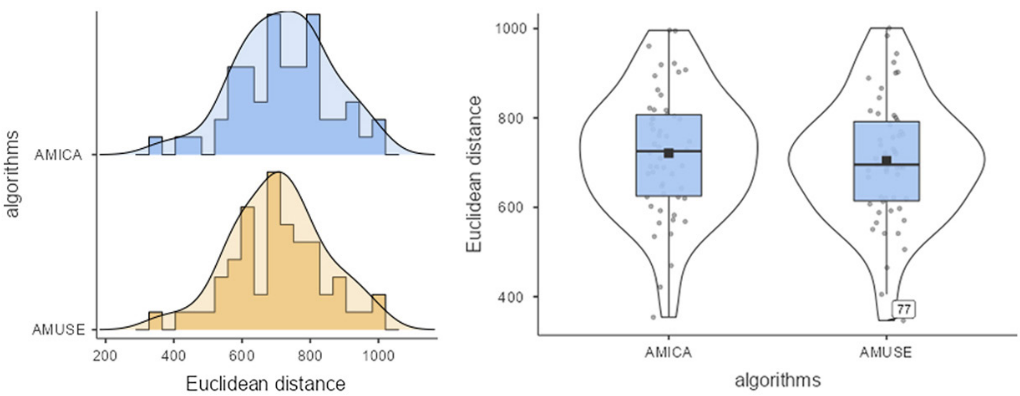


**Fig. 4.** Values of the Euclidean distance between the cleaned and real EEG signals for each of the two techniques

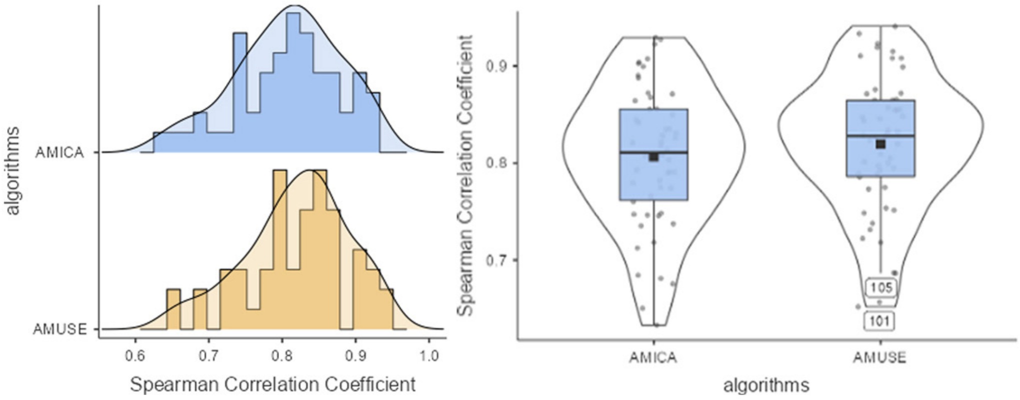


**Fig. 5.** The Spearman CC values computed between the VMD-BSS produced EEG signals and the true ones

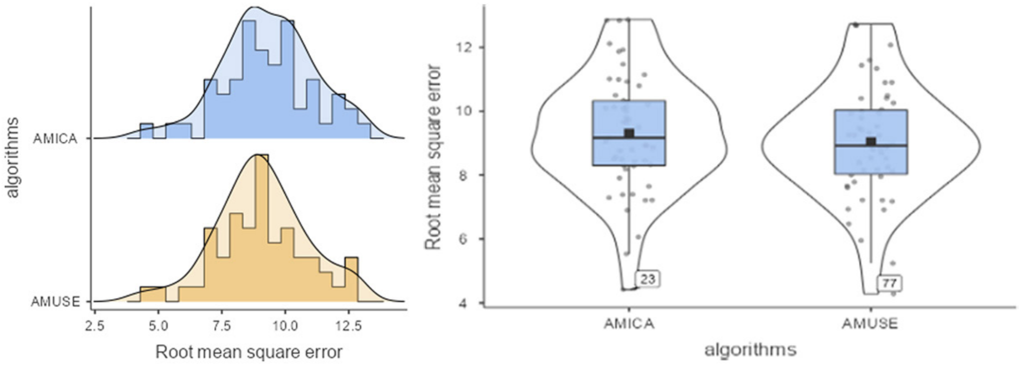


**Fig. 6.** The clean reconstructed signal's root means square error (RMSE) values following the application of the two hybrid algorithms

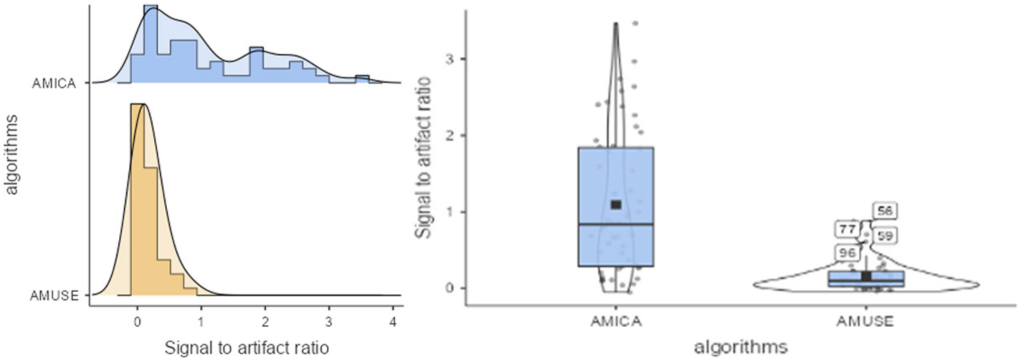


**Fig. 7.** A calculation of the signal-to-artifact ratio using the polluted, cleaned, and real EEG records

After conducting a thorough analysis of the performance of AMICA and AMUSE algorithms when integrated with the Variational Mode Decomposition (VMD) technique and assessing them across multiple performance metrics, we can draw meaningful comparisons. The Kruskal-Wallis test results revealed that there were no significant differences in performance between the combined algorithms concerning Euclidean distance ($\chi^2 = 0.571$, df = 1, p = 0.450), Spearman Correlation Coefficient ($\chi^2 = 1.028$, df = 1, p = 0.311), and Root Mean Square Error ($\chi^2 = 0.761$, df = 1, p = 0.383). These findings suggest that, when coupled with VMD, both algorithms exhibited similar performance across these particular metrics. However, a notable difference emerged when evaluating the Signal to Artifact Ratio, a critical metric for various applications. A significant difference was evident ($\chi^2 = 42.501$, df = 1, $p < .001$), indicating substantial variability in the performance of the combined algorithms in this regard. The effect size ($\varepsilon^2$) ranged from 0.00534 to 0.39720 across these metrics, signifying varying magnitudes of impact.

To further scrutinize these distinctions, we employed the One-Way ANOVA test using both Welch's and Fisher's methods. For Euclidean distance, Spearman Correlation Coefficient, and Root Mean Square Error, neither Welch's nor Fisher's test identified any significant differences ($p > 0.05$) between the combined algorithms, thus corroborating the Kruskal-Wallis findings. However, for the Signal to Artifact Ratio, both Welch's and Fisher's tests revealed a highly significant difference ($p < .001$), emphasizing that the amalgamation of these algorithms with VMD substantially impacted their performance in this specific metric.

Considering all of these results, it is safe to conclude that, within this particular context and with the Signal to Artifact Ratio as a pivotal performance criterion, AMICA stands out as the preferred algorithm. It outperforms AMUSE in effectively distinguishing and isolating signals from artifacts when used in conjunction with VMD. Nevertheless, it is essential to highlight that the choice of algorithm should always be guided by the specific requirements and objectives of your application, as different metrics and contexts may favour one algorithm over the other.

Furthermore, when examining individual patient data, AMUSE exhibits a slightly stronger positive correlation, as indicated by the higher Spearman correlation coefficient (0.8196), compared to AMICA (0.8068). Additionally, the data points in AMUSE are more tightly clustered, as evidenced by the slightly lower Euclidean distance (704.3926) in comparison to AMICA (721.2634). Furthermore, AMUSE demonstrates a marginally lower Root Mean Square Error (RMSE) of 9.0467, suggesting improved predictive accuracy. However, it is noteworthy that AMICA excels in noise reduction, boasting a significantly higher Signal to Artifact Ratio (SAR) of 1.0924, in contrast to AMUSE (0.1653). Therefore, the choice between these methods should align with the specific objectives of the analysis: AMUSE prioritizes correlation and accuracy, whereas AMICA is better suited for tasks requiring superior noise reduction capabilities.

**Table 2.** Analysis of performance evaluation results derived from previous research on mitigating ocular artifacts in EEG recordings

| Study | Method | Evaluation Criteria | Results |
|---|---|---|---|
| [32] | Single-channel blind source separation method based on variational mode decomposition | Correlation coefficient | 0.76 |
| [33] | Level 2 Dynamic Segmentation wICA | Root mean square error | 9.59 (for subject 1) |
| [13] | BSS | Euclidean distance | $3.25 \cdot 10^3$ with VEOG, $4.16 \cdot 10^3$ with HEOG |
| [34] | EMD-FastICA | SAR | 1.04761 |

In Table 2, we have presented a compilation of previous research endeavours focusing on artifact removal methodologies, all of which have been assessed based on criteria similar to ours. It is essential to acknowledge that undertaking direct comparisons between our approach and these methodologies poses significant challenges. This complexity arises from the fact that each technique has been uniquely applied within diverse datasets and with specific sets of parameters, making direct comparisons less straightforward.

In the realm of artifact removal methodologies, the work of Zhang et al. [32] stands out for its specialized focus on capturing aero acoustic signals from wind turbines. Their innovative approach, utilizing Variational Mode Decomposition (VMD) within the Single-Channel Blind Source Separation (SCBSS) framework, exhibits remarkable efficacy in isolating wind turbine aero acoustic sounds. This unique application addresses a specific and challenging signal separation scenario, showcasing the adaptability of VMD in diverse contexts.

Turning to the study by Sheoran et al. [33], the integration of Canonical Correlation Analysis (CCA) and Noise Adjusted Principal Component Transform (NAPCT) in their methodology represents a noteworthy advancement in the field. Their emphasis on eliminating eye movement artifacts in EEG data without manual intervention is a distinctive contribution. This automated approach not only streamlines the artifact removal process but also introduces efficiency and reliability into the analysis, marking a notable departure from labour-intensive techniques.

Soomro et al.'s [34] work introduces a technique that combines Empirical Mode Decomposition (EMD) with Independent Component Analysis (ICA) for the automatic elimination of eye blink artifacts from EEG. What sets this methodology apart is its demonstrated effectiveness across both simulated and actual EEG datasets. The trustworthy artifact reduction achieved by Soomro et al. underscores the practical applicability of their approach, providing a robust solution for artifact mitigation in diverse real-world scenarios.

In comparison, our proposed methodology contributes significantly to the field by integrating VMD and BSS techniques, coupled with a hard thresholding approach. This hybrid strategy offers a unique synergy, leveraging the adaptability of VMD to non-linear and non-stationary EEG data and the source separation proficiency of BSS. The incorporation of a hard thresholding step further enhances artifact elimination. Our methodology addresses the challenge of ocular disturbances in EEG signals, presenting a comprehensive solution that prioritizes the SAR. This emphasis on a critical performance metric, along with the distinctive combination of techniques, distinguishes our contribution from existing methodologies, paving the way for improved artifact removal in EEG signal processing.

## 4 CONCLUSION

In conclusion, our research project has been motivated by the overarching objective of improving the elimination of ocular disturbances from EEG data—a crucial step in the accurate interpretation and analysis of brain activity. To achieve this, we developed a novel hybrid strategy that integrates BSS algorithms with VMD. The incorporation of VMD into our technique offers several distinct advantages. VMD excels in handling non-stationary and non-linear signals, critical components of EEG data. It surpasses traditional decomposition techniques in capturing the intricate dynamics and complexity observed in brain activity. Furthermore, VMD addresses the "endpoint effect" and mode mixing, two significant challenges in EEG artifact elimination, thereby enhancing the overall effectiveness of artifact removal. Importantly, VMD not only enhances the flexibility and resilience of our methodology but also ensures the preservation of crucial brain information throughout the artifact removal process. This preservation is vital for accurate EEG analysis, enabling the diagnosis of neurological illnesses, comprehension of cognitive processes, and advancement of neuroscience research.

Turning to the evaluation of the techniques employed, our comprehensive assessment unequivocally demonstrates that AMICA, a higher-order statistics (HOS) algorithm, emerges as the preferred choice in the specific context of this study, using the SAR as the primary performance parameter. When coupled with VMD, AMICA consistently outperforms AMUSE, a second-order statistics (SOS) method, due to its superior ability to distinguish between real brain signals and artifacts. However, it is crucial to emphasize that the specific goals and requirements of the current study should guide the selection of the most suitable approach.

In conclusion, this study underscores the critical role of artifact removal in processing EEG signals. To significantly enhance the effectiveness of artifact removal, particularly in the context of SAR, it proposes a potent hybrid approach that leverages the inherent strengths of VMD and BSS algorithms. The addition of VMD improves the flexibility, resilience, and fidelity of EEG data preprocessing, ultimately enhancing the accuracy and reliability of EEG signal analysis as a whole. This study not only contributes to our understanding of brain activity and cognitive processes but also underscores the importance of selecting the best methodology based on the study's objectives. Our hybrid technique represents a significant advancement in the rapidly changing field of EEG signal processing, with the potential to advance both clinical and neuroscience applications.

The decision to adopt a hybrid strategy, fusing Variational Mode Decomposition (VMD) with Blind Source Separation (BSS), specifically AMICA and AMUSE, is grounded in the unique strengths each method brings to the intricate task of artifact removal in EEG signals. the selection of VMD is driven by its innate adaptability to the non-linear and non-stationary attributes of EEG data, providing a versatile means to capture complex patterns in brain signals. Moreover, VMD tackles prevalent challenges like mode mixing and the 'endpoint effect,' heightening the precision of signal decomposition and reconstruction. The integration of BSS, recognized for its adeptness in isolating independent sources—especially distinguishing neural signals from artifacts—complements VMD's preprocessing capabilities. The hybrid approach strives to furnish a comprehensive solution by not only adeptly preprocessing data but also prioritizing the augmentation of the Signal to Artifact Ratio (SAR). While acknowledging the presence of alternative techniques for artifact removal, the chosen VMD-BSS hybrid method presents a distinctive and robust methodology, tactically combining VMD's adaptability with the source separation effectiveness of BSS to comprehensively address artifacts in EEG signals.

While this study primarily focuses on resting-state EEG, we recognize the importance of addressing artifacts related to task-oriented EEG. The hybrid approach of combining VMD with BSS is designed to handle various artifacts, including those introduced during specific tasks. We have conducted an initial evaluation of its performance in task-oriented scenarios, with a focus on enhancing the SAR and isolating neural signals from task-related artifacts. Further exploration and validation in task-oriented EEG contexts are essential to ensure the method's robustness and applicability in scenarios involving specific tasks.

Exploring the reverse application of our hybrid approach is a promising avenue for future research. This entails initiating the procedure using BSS for the initial separation of the EEG signals, followed by using VMD to break down each independent component into Intrinsic Mode Functions (IMFs) to refine the data. Additionally, investigating alternative single-channel decomposition methods, such as wavelet transforms, provides a means to gain fresh perspectives and potentially enhance decomposition precision. Furthermore, the utilization of advanced artificial intelligence (AI) algorithms represents a potential frontier, offering opportunities for improved signal separation techniques.

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