# EEG Artifacts Removal: A Detailed Review Based Study

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**Abstract:**
Electroencephalography, or EEG for short, is a technique used to record the electrical activity of the brain. This EEG detects errors that affect how the human brain functions. This method is the most commonly used for recording the brain in laboratory research, clinical investigations, patient health monitoring, diagnostics, and a variety of other applications due to its non-invasiveness and cost-benefit ratio. Most EEG recordings are contaminated by a variety of irregularities, including those caused by electrode displacement, motion, ocular, and muscular activity-related EMG anomalies. These unwanted artifacts may make it difficult to distinguish genuine information from them, in addition to confusing the brain's information processing that supports them. EEG signal artifacts can be removed in a variety of ways. The top and most popular artifact reduction techniques are listed on this page as PCA, pure EEG, and wavelet transform. The study provides a thorough evaluation of current artifact identification and removal methods from scalp EEG for all conceivable EEG-based applications.

**Keywords: EEG, Artifacts, Artifacts Removal, PCA, BSS, Wavelet**

## I. INTRODUCTION

The electroencephalogram is a recording of electrical activity in the brain. The electrical activity is represented by a waveform. Cortical electrical activity is reflected in the waveform. EEG refers to the measurement of spontaneous brain activity. The signal intensity is very low and is measured in microvolts (V) when measured on the scalp and millivolts (MV) when measured on the brain's surface. The bandwidth of the EEG wave is 1 Hz to 50 Hz, as shown in fig.2. The waveforms' frequencies are delta, theta, alpha, and beta. Fig.1. depicts the EEG signal with its various waves. The frequency of the delta wave is 3 Hz or less. This wave is the slowest and has the most amplitude. This wave is present in adults frontally and posteriorly in children. Theta waves have a frequency range of 3.5 to 7.5 Hz. This wave is considered slow activity. This wave is abnormal in adults who are awake and normal in adults and children up to the age of 13. The alpha wave has a frequency of about 7.5 to 13 Hz and can be seen in the posterior regions of the brain on both sides. The amplitude of this wave is greater on the dominant side. This wave cannot be seen when the eyes are open or the brain is thinking or calculating, but it can be seen when the eyes are closed and the brain is relaxing.

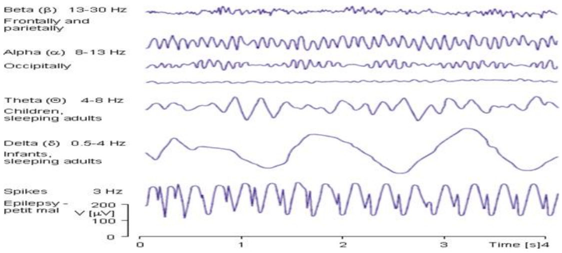

Fig. 1. EEG signal with its different waves.
Source: Research Gate

The beta wave is a fast-activity wave. This wave has a frequency equal to or greater than 14 Hz, as seen on both sides of the symmetrical distribution when viewed frontally. When disease-affected patients are alert or anxious, or when their eyes are open, this wave has a dominant rhythm.

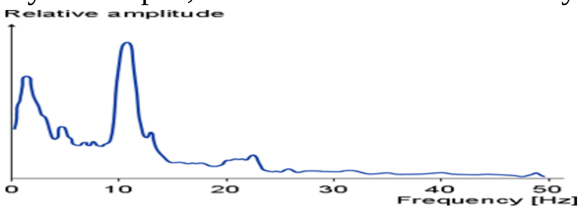

Fig. 2. Frequency spectrum of normal EEG signal
Source: Oxford University Press

Artifacts in EEG recordings can come from a variety of sources. EEG artifacts can affect recordings across a wide frequency range in both the temporal and spectral domains, and they can be caused by both internal and external factors. Movement and physiological activity (such as ECG, EMG/muscle artifacts, and EOG) are the internal causes of artifacts. Environmental interferences, recording devices, electrode pop-ups, and cable movement are all examples of external sources of artifacts. Furthermore, while some artifacts can be seen in multiple nearby channels, others can only be seen in one, and some artifacts can be seen globally (local). Furthermore, while some abnormalities appear to be regular, periodic phenomena, such as ECG or pulse artifacts, others may be extremely chaotic. The first and most important step in treating and removing EEG artifacts is identifying them.

## II. LITRETURE REVIEW

The usefulness or accuracy of any diagnostic or detection of information connected with EEG signals, according to Malik M. Naeem Mannan et al. [1], is governed by the degree to which the signal is polluted or devoid of undesired signals, such as artifacts, etc. Artifact removal determines how clearly signal-related features can be retrieved. Nevertheless, whatever low-pass frequency restrictions are suitable for EOG signals has yet to be discovered. In this study, the author aims to eliminate polluted bidirectional artifacts by low-pass filtering the EOG signals before utilizing them in the artifact removal procedure. Using 15 purposely polluted EEG and EOG datasets, this study investigated the optimal EOG signal filtering limits using the most modern artifact removal algorithms. For both simulated and real-world EEG datasets, 12 different low-pass filters were applied to EOG signals using 5 different algorithms, including simple regression, least-squares, recursive least squares, REGICA, and AIR. The findings were evaluated using mean square error, mutual information, signal-to-artifact ratio, and mean absolute error.

EEG signal artifacts were detected and eliminated by Malik Muhammad Naeem Manna et al. [2]. Depending on the source of the signal, artifacts can be classed as physiological or non-physiological signals. To validate data for hybrid approaches, such as combinations of the aforementioned methods, blind source separation (BSS), canonical correlation analysis (CCA), independent component analysis (ICA), morphological component analysis (MCA), wavelet transform, and signal space projection are utilized.

In order to increase classification accuracy, Manoj Thulasidas et al. [4] employed an SVM classifier to properly categorize data from nine healthy persons. F. Lotte and colleagues [5] investigate the classification algorithms used in brain-computer interfaces. A full examination of the classifiers used in BCI is presented, along with advice for selecting a classifier and a comparison of classification accuracy. Gajic et al. [6] define an automated categorization of EEG for epilepsy diagnosis using wavelet transformations and statistical pattern recognition. The wavelet transform is used to extract features, the size of the feature space is lowered, a quadratic classifier is employed to classify, and an accuracy of 99% is obtained. Nonlinear series analysis is not carried out as effectively as it should be in order to enhance classification. A slight change in the EEG signal should also be noticed and offer the accurate illness diagnostic term.

Artifact removal approaches such as artifactual segment rejection, regression, time-frequency representation, and adaptive filtering are only used seldom by certain researchers. Wavelet Transform, Empirical-Mode Decomposition, Independent Component Analysis, and Blind Source Separation, as previously indicated, are common removal strategies employed by researchers nowadays. This study looks at and compares existing methods. The second section goes through several artifact removal approaches and algorithms. We compare the various artifact removal strategies in the third part. The fourth portion brought the review to a close.

## III. DIFFERENT TECHNIQUES FOR ARTIFACT REMOVAL

A. Separation of Blind Sources (BSS)

Blind source separation (BSS), a method based on this, is one of the most widely used artifact removal methods. BSS seeks to extract certain unknown source signals from their mixes in order to estimate the unknown mixing channels using just the data currently present in the mixtures. It is revealed at the output of each channel that there is little to no knowledge of the source signals and the mixing channel [3].

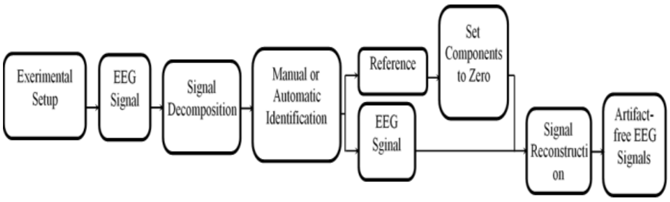


Fig. 3. General Schematic of BSS Algorithms
Source: Elsevier

The key advantage of this approach is that no prior expertise of mixing diverse sources is required. The main concept of the technique for blind source separation is shown in Figure 3. Initially, the EEG signal is disassembled, and artifacts are either manually or automatically recognized. The BSS approach delivers an artifact-free EEG signal that compares favorably to the reference EEG signal after artifact removal and reconstruction. Assume that X denotes multichannel EEG signals with linear source mixing (S).

$$X = AS \quad (1)$$

where A represents the mixing matrix. This algorithm is used to generate an un-mixing matrix W for separating the original sources

$$\hat{S} = WX \quad (2)$$

where Sˆ, denotes the sources' estimation. To eliminate artifacts from EEG data, BSS techniques such as independent component analysis, principal component analysis, canonical correlation analysis, and morphological component analysis have been developed.

### A. Independent Component Analysis

This has been routinely used to differentiate signals obtained from many sources. The de-mixing or separation approach [4] is applied, which is based on the linear transformation of the mixed signal into as statistically independent components as feasible. One of the BSS algorithms uses this to separate the discrete components of multichannel EEG data from diverse sources (ICs). This has become an important technique for eliminating artifacts from EEG data. ICA does not require any prior expertise to remove artifacts. The mixing matrix and statistical independence of the sources serve as the foundation for the ICA. The data given into the algorithm has a significant impact on the accuracy of artifact removal data. Depending on the researchers' degree of competence, topography maps and IC time series can be utilized to choose artifactual components. Researchers have uncovered a variety of traits that may automatically distinguish fake components. These automatically recognized components have been shown to be useful at lowering computation costs and artifacts. Because neural information was eliminated, several artifactual ICs remain unsolved. Another difficulty is that only one channel may use the ICA.

### B. Empirical Mode Decomposition

It was designed to operate with stochastic non-stationary systems and is empirical and data-driven. As a result, it is ideal for processing and analyzing EEG signals. EMD's computational complexity is significantly higher in comparison. This may or may not apply to online application submissions. EMD theory is still in its infancy, hence it is difficult to say if it would be robust across all EEG recordings [5]. Time-domain signal decomposition into a group of intrinsic mode functions (IMFs). Each IMFs must follow two major conditions:

- The number of extrema and number of zero crossing must be equal.
- The mean value of the envelopes defined by local minima and local maxima must be zero.
  Following algorithm is used to compute the artifact removal:
- Find the local maximum and minimum of the provided data.
- Upper envelope is estimated for maxima and lower envelope is estimated for minima using cubic interpolation.
- The estimated mean of the two envelopes is removed from the supplied data.
- Up until the halting criteria are satisfied, repeat steps 1 through 3.

The decomposed signal can be represented as

$$S(t) = \sum_{i=1}^{p} d_i(t) + r(t) \quad (3)$$

where p is indeed the total number of IMFs and d is the number of IMFs. Instead of using manual parameters, the decomposition in this approach is adaptively formed from data. As a result, the EMD outperforms the FT and WT. The majority of EMD is used by researchers for ocular artefacts. EMD is extremely noise sensitive.

### C. Wavelet Transform

Wavelet-based approaches are currently being used to remove EEG artefacts in order to obtain high frequency resolution across all frequencies [6][9][10]. Due to its proportionate resolution for each frequency band, this wavelet transform is suitable for EEG signals. Analysis of non-stationary biological data frequently use the wavelet transform, a potent denoising tool (WT). This technique may localise in both the temporal and frequency domains, making it the most unique. An EEG signal can be cleaned up using this to get rid of EMG and EOG artefacts.

The wavelet transform represents the base wavelet function and the time-domain signal. The discrete wavelet transform (DWT) is utilized for discrete signals; a set of basis function is defined on dyadic grid in time-scale plane as

$$\psi_{i,j}(t) = 2^{-\frac{j}{2}}\psi(2^{-j}t - k) \quad (4)$$

where j governs the amount of scaling and k represents the amount time shifting. In DWT, successive low pass and high pass filters are used to decompose the high-frequency and low-frequency components. The algorithm is given below to compute DWT for EEG signal.

- Break down the EEG signal into a number of specific components.
- Threshold details coefficients are used to denoise signals and remove artifacts.
- Rebuild an artifact-free EEG signal by removing threshold components.

Presently, WT is widely used for artifact removal from EEG data. Moreover, the WT is robust and versatile for biomedical applications. Basically, WT is used as a tool to denoise EEG signals. The major disadvantage of this method is that the artifacts cannot be completely removed if the signals overlap.

### D. Pure EEG

This is an innovative method for removing artifacts from long-term EEG recordings. This has a lengthy development and evaluation history [7]. The method employs an iterative Bayesian estimation procedure and is founded on a neurophysiological model. This method for removing EEG artifacts successfully improves the readability of EEGs with artifact issues. The "Pure-EEG" method has the advantages of being completely automatic, having a clear view of patterns in all situations, and being adaptable to a wide variety of artifacts. The EEG vector e(t) is decomposed into three superposition components

$$e(t) = e_j(t) + e_a(t) + n(t) \quad (5)$$

where $e_j(t)$ - ‘‘true EEG’ the signals coming from cerebral source, $e_a(t)$ - the artifact vectors the signal coming from various artifacts, n(t) - noise vector coming due to various process like analog-to-digital converter, amplification, etc.

$$p_j(t) = L_j(t) \quad (6)$$

where L is lead filed matrix, $p_j(t)$ is electric potential on the electrodes.

$$e_j(t) = Mp_j(t) \quad (7)$$

where M is K × L montage matrix, in which each row is representing an EEG channel.

$$C_{\hat{e}}(v) = MLC_{\hat{j}}(v)L^T M^T \quad (8)$$

where $C_{\hat{e}}(v)$= Correlation matrix of $\hat{e}_{\hat{j}(v)}$

$C_{\hat{j}}(v)$- source current densities of j

$$C_{\hat{j}}(v) = C_{\hat{j}}^t(v)C_{\hat{j}}^s \quad (9)$$

Where $C_{\hat{j}}^t$ and $C_{\hat{j}}^s$ characterize temporal and spatial correlations, respectively.

$$e_a(t) = Ma(t) \tag{10}$$

where M is the montage matrix and a(t) is a length – L artifact vector that models all the artifacts occurring1at1one or more electrodes. In the frequency domain the correlation matrix $C_{\hat{e}a}(v)$ can be written as

$$C_{\hat{e}a}(v) = MC_{\hat{a}}(v)M^T \tag{11}$$

The PureEEG is used to remove the artifacts effectively and improves the readability of EEG signal which are affected by artifacts. Minute drawback of this algorithm is the EEG signal pattern attenuates in rare conditions. It is an important tool for the EEG artifact removal technique.

## E. Principal Component Analysis (PCA)

The EEG signal is having more dimension as a huge amount of datasets is present. To reduce the dimensionality of the dataset, the principal component analysis is used. The dimension is reduced by the formation of basis vectors. The linear combination of vector is recreated using basis vectors from a dataset. Consider an example with 3-dimension basis vector:

$$\begin{pmatrix}1\\0\\0\end{pmatrix}, \begin{pmatrix}0\\1\\0\end{pmatrix}, \begin{pmatrix}0\\0\\1\end{pmatrix} \tag{12}$$

and the sample vector is given as:

$$\begin{pmatrix}2\\3\\5\end{pmatrix} \tag{13}$$

By using linear combination of basis vector the reconstructed vector is:

$$\begin{pmatrix}2\\3\\5\end{pmatrix} = 2 * \begin{pmatrix}1\\0\\0\end{pmatrix} + 3 * \begin{pmatrix}0\\1\\0\end{pmatrix} + 5 * \begin{pmatrix}0\\0\\1\end{pmatrix} \tag{14}$$

By doing this the dataset is transformed into a new set of variables which are called principal components. These principal components are uncorrelated. Steps involved in principal component analysis

- Step 1: Reducing the data from m-dimensional to n-dimension and compute covariance matrix using equation

  $$C = \left(\frac{1}{t}\right) \sum_{t=1}^{l} x_t * x_t^T \tag{15}$$

- Step 2: Compute eigenvectors of matrix C.
- Step 3: Find singular value decomposition using [U, S, V] = svd (C).
- Step 4: U, S, and V are matrices, where U is [m x m] matrix. To reduce system from m-dimensions to n-dimensions to take the first n-vectors from U of first 'n' column
  $U = [U^{(1)}U^{(2)} \dots \dots \dots U^{(n)}]$
- Step 5: Take a first 'n' columns of the 'u' matrix and stack in columns, where n x m matrix this is called $U_{reduce}$.
- Step 6: Calculate 'k' as follows the $k = (U_{reduce})^T * x$ so, $[n \times m] * [m \times 1]$ which generates matrix which is a n * 1.

The principal component is applied to a raw data. The EEG signal recorded which is used for analysis is a raw data. This raw data is given to the PCA algorithm to detect the epilepsy disease using PCA algorithm. The PCA algorithm returns the coefficients of the components which are called as loadings for any m x n matrix. The row of the input data corresponds to the observation and the columns corresponds to variables. The output of the PCA is n x n matrix. The output matrix column contains coefficients for one principal component. In this singular value decomposition is used as the algorithm which supports PCA to normalize the data. Algorithm steps are explained as follows:

- Step 1: Input data to compute PCA.
- Step 2: By default, SVD is selected, in case different algorithm can be set and the algorithms are eigenvalue decomposition and alternating least square algorithm.

The signal is split into orthogonal components using the direction with the greatest fluctuation. PCA obviously accomplishes independence when correlated data are transformed into uncorrelated variables. The following axes are set up in decreasing order of data variability, with PC1 standing in for considerable data variability (i.e., data that is noisy and uncorrelated) (lowest variance indicates the redundant data).

## IV. EVALUATION PARAMETERS FOR COMPARISION OF DIFFERENT ARTIFACT REMOVAL ALGORITHM TECHNIQUES

In this study, we gathered a set of assessment metrics that have previously been utilized and validated in previous research publications to evaluate artifact removal approaches using actual and simulated signals. Although testing these algorithms using simulated signals is easier, testing them with real signals has shown to be more reliable. Additionally, because true EEG signals are non-stationary, comparing algorithms using the same EEG data is possible. The metrics listed below can be used to evaluate the performance of various artifact removal approaches that employ simulated EEG data. Table I lists the performance metrics that may be used to compare different artifact removal methods.

TABLE I.
PERFORMANCE METRICS

| Sl. No. | Evaluation Parameters | |
|---|---|---|
| | ***Performance Metrix*** | ***Formula*** |
| 1 | Mean square error (MSE) | $^{1}/_{\mathrm{N}} \sum_{\mathrm{n}=0}^{\mathrm{N}-1} [x(n) - x\hat{}(n)]^{2}$ |
| 2 | Peak signal to noise ratio (PSNR) | $10\log_{10}\frac{(\max)^2}{\mathrm{MSE}}$ |
| 3 | Relative root mean square error (RRMSE) | $\frac{\sqrt{\mathrm{MSE}}}{\frac{1}{\mathrm{N}}\sum_{\mathrm{n}=0}^{\mathrm{N}-1} x(\mathrm{n})}$ |
| 4 | Correlation coefficient (CC) | $\frac{cov[x(n), x\hat{}(n)]}{\sigma x(n)\sigma x\hat{}(n)}$ |
| 5 | Mean absolute error (MAE) | $^{1}/_{\mathrm{N}} \sum_{\mathrm{n}=0}^{\mathrm{N}-1} \lvert x(n) - x\hat{}(n)\rvert$ |
| 6 | Signal to noise ratio (SNR) | $10\log_{10}\frac{(x(n}{[[x(n) -}$ |

a. where; x(n)=clean EEG signal, x^(n)= estimated (denoised) EEG signal N = total length of signal, max = maximum amplitude value of x(n) Cov = covariance, σ = standard deviation

## V. COMPARATIVE ANALYSIS OF DIFFERENT ALGORITHMS

This review paper presents a novel comparative analysis of various artefact removal techniques, as well as a detailed and insightful table that builds on previous research to highlight the strengths and limitations of each algorithm. The comparative analysis is indicated in Table II

TABLE II.
**COMPARATIVE ANALYSIS OF DIFFERENT ALGORITHMS**

| **Sl. No.** | **ANLYSIS** | |
|---|---|---|
| | ***Algorithm Name*** | ***Highlights of the method*** |
| 1 | Blind source separation | Epileptic monitoring is performed with the help of this automated and multi-channel method. |
| 2 | Independent component analysis | This BSS method simply separates multichannel EEG data from various sources into discrete components (ICs). It is a strategy for conducting research into temporal domains. The primary drawbacks in this scenario are the high computational complexity and the need for manual selection of artificial integrated circuits. |

| Sl. No. | ANLYSIS | |
|---|---|---|
| | ***Algorithm Name*** | ***Highlights of the method*** |
| 3 | Empirical mode decomposition | This method is automatic, multi-channel method used in BCI. |
| 4 | Wavelet Transform | This approach, which uses many channels and is automatic to remove artefacts, is significant. It possesses time- and frequency-domain localization properties. Patients with VaD and MCI linked to stroke both employ this technique often. |
| 5 | Pure EEG | This totally automatic, multi-channel technique is utilized to get rid of a variety of artefacts, including line noise, myogenic artefacts, electrode artefacts, and movement artefacts. In virtually all circumstances, it basically provides a clear pattern. This approach is the |

| Sl. No. | ANLYSIS | |
|---|---|---|
| | ***Algorithm Name*** | ***Highlights of the method*** |
| 6 | Principle Component Analysis | most popular since it is very computationally efficient. One of the greatest techniques for artefact removal is this one. It uses a multi-channel method and is automatic. The input signal's dimension is reduced via principal component analysis. The EEG signal is subsequently analyzed using the reduced dimension. It uses time domain analysis. |

**VI. CONCLUSION**

The medical field's advancement has increased the need for the most effective illness treatment approaches. One approach for assessing brain activity is electroencephalography (EEG). When electrodes are placed on the brain's scalp, this approach of diagnosing brain activity is successful. Significant nonlinearity or artifacts, on the other hand, typically have an influence on this. These artifacts must be missing in order to create an accurate diagnostic report. The goal of this article is to offer a clear review of the strategies used to remove EEG artifacts. By discussing the benefits and drawbacks of the various artifact removal approaches.

We have presented several novel contributions to the field of artefact removal in EEG signal processing in this review paper. For starters, our comprehensive comparison table on different artifact removal algorithms provides an insightful analysis of the strengths and limitations of various artefact removal techniques that has not been presented in such a way in the literature. Second, as a novel contribution to the field, we identified the best techniques for artefact removal as PCA, PURE EEG, and Wavelet

Transform. We have concluded that PCA, pure EEG, and wavelet transform are the most effective approaches for artifact removal due to their high efficiency, flexibility, and novelty. Finally, our paper combines a detailed review of both artefact removal techniques and performance metrics for evaluating the artefact removal algorithm, providing a comprehensive overview that has not previously been presented in such depth. In conclusion, our paper makes a valuable and distinct contribution to the field of artefact removal, serving as a useful guide for researchers and practitioners.

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