International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 29, No. 1, February, 2024, pp. 247-252
Journal homepage: http://iieta.org/journals/isi

A Review of EEG Artifact Removal Methods for Brain-Computer Interface Applications

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https://doi.org/10.18280/isi.290124

Received: 10 July 2023
Revised: 20 November 2023
Accepted: 31 December 2023
Available online: 27 February 2024

Keywords:
electroencephalogram (EEG), brain-computer interface (BCI), artifact removal, Principal Component Analysis (PCA), wavelet convolution

ABSTRACT

The use of electroencephalogram signals in brain-computer interface Applications is widely used in Neuroscience. EEG records electrical activity in the brain but can also capture unwanted electrical activities called artifacts. They can originate from environmental noise, experimental errors, and physiological sources. To address these challenges, EEG Data Analysis involves different data preprocessing and statistical techniques. This systematic review conducted on more than 25 papers, aims to provide an overview of various types of artifacts such as extrinsic and intrinsic artifacts and methods available for removing those artifacts from EEG signals. Each approach presents unique advantages and challenges, contributing to the enhancement of the quality and reliability of EEG data for accurate analysis and interpretation.

1. INTRODUCTION

Brain wave analysis, a field of study spanning several decades, has made significant strides in understanding brain function through the study of electrical activities of our brain [1].This progress has led to valuable insights into cognitive processes, emotional states, and neurological disorders, impacting fields such as psychology, medicine, human-computer interaction [2-4]. Nonetheless, the presence of artifacts poses a challenge in the examination of brain wave signals. This review seeks to discuss some of the frequently employed techniques for the elimination of artifacts from these signals.

Artifacts can distort the genuine neural activity, leading to misinterpretation of the underlying brain signals. They may introduce spurious patterns that can compromise the accuracy of quantitative EEG measures. Additionally, the diverse nature of artifacts, such as those stemming from muscle activity, eye movements, or external interferences, makes their identification and removal a complex task. Furthermore, in real-world scenarios, it is often difficult to eliminate all artifacts, necessitating the development of robust methods to minimize their impact on the reliability and validity of EEG data.

The research in EEG analysis has not only advanced our understanding of brain function but also expanded its applications across various domains [5, 6]. The utilization of these methods in brain-computer interfaces (BCIs) enables researchers to conduct more precise analysis of brain signals and explore the impact of mental states on BCI data. By employing advanced artifact removal techniques, researchers can effectively clean EEG signals, reducing noise and unwanted electrical activities that may interfere with the accuracy of BCI analysis [7]. This, in turn, allows for a more thorough investigation into the relationship between mental states and BCI performance. Through the use of machine learning, deep learning, and statistical approaches, researchers can uncover valuable insights into how different mental states that influence the patterns and characteristics of EEG signals recorded in BCIs [8]. The ability to extract meaningful information from EEG data while minimizing artifacts significantly enhances the precision and reliability of BCI research. In addition to its applications in BCI, EEG plays a pivotal role in the fields of Neurofeedback and Brain Training. Neurofeedback and Brain Training heavily rely on the use of EEG to gain deeper understanding and control over brain activity. By employing EEG analysis researchers can gain valuable insights into the intricate workings of the brain, allowing for targeted interventions and customized training programs which are helpful for Anxiety and Post-Traumatic Stress Disorders [9, 10].

One of the primary challenges encountered in EEG analysis is the presence of noise or artifacts in the acquired signals, which can hinder accurate interpretation and analysis. Artifacts can originate from various sources, both external and internal to the body, and their removal or mitigation is crucial for reliable EEG analysis [11]. In recent years, significant efforts have been made to develop advanced artifact removal methods using machine learning deep learning and statistical approaches.

2. LITERATURE REVIEW

2.1 Artifacts

EEG recordings capture electrical signals from the brain including ECG, EOG, and EMG, but they also include other unwanted electrical activities known as artifacts. Removing EMG artifacts poses a challenge due to their higher amplitude, wide frequency spectrum, and broad anatomical distribution. These artifacts can arise from various muscle movements near the head. EMG artifacts have a wide frequency range and can be observed across different locations on the scalp. ECG and EOG artifacts are more confined to specific areas and can be effectively eliminated using reference channels. However, removing EMG artifacts using reference channels is challenging due to their intricate distribution across multiple muscles [12].

Artifacts in EEG data can have a negative impact on its quality, and it is important to understand the different types of artifacts in order to effectively remove them. Artifacts can originate from environmental noise, experimental errors, and physiological sources.

Extrinsic Artifacts: These artifacts come from external factors such as the environment and experimental errors. They can be classified as follows:

- Environmental Artifacts: These artifacts can be eliminated using simple filtering techniques since their frequency is inconsistent with the desired EEG signals.
- Experimental Errors: Proper procedures and planning can help reduce experimental errors, making them relatively easier to address.
- Instrument Artifacts: These artifacts arise from electrode misplacement and cable movements. They can be mitigated through proper procedures and planning.
- Electromagnetic Interference: External electromagnetic interference from the surroundings can affect EEG recordings. However, such artifacts can be easily filtered out due to their distinguishable frequency band.
- Volume Conduct Artifact: These artifacts can be introduced due to the coherence between channels while observing brain activity across multiple different channels. Techniques such as Independent Components Analysis can be used to address this type of artifact [13].

Intrinsic Artifacts: These artifacts arise from physiological sources within the body. They are more challenging to remove and often require specific algorithms. The major physiological artifacts affecting EEG data include:

- Ocular Artifacts: Ocular artifacts are significant sources of artifacts in EEG recordings. They are caused by eye blinks and eye movements, which can spread over the scalp to affect EEG activity. These artifacts result from changes in the orientation of the retina and cornea dipole during eye movements, as well as ocular conductance due to the contact between the cornea and eyelid during blinks. Ocular artifacts can contaminate both EEG and electrooculogram (EOG) signals. Removing these artifacts can be challenging due to bidirectional interference between EEG and EOG.
- Muscle Artifacts: Muscle activity can contaminate EEG data and poses a difficult problem to address. Muscle artifacts can be caused by the contraction and stretch of muscles in proximity to the signal recording sites, as well as actions like talking, sniffs, and swallowing. These artifacts have a broad frequency distribution and are measured using electromyogram (EMG). They are particularly challenging to eliminate due to the statistical independence between EMG and EEG signals.
- Cardiac Artifacts: They may occur when electrodes are positioned directly on or in close proximity to blood vessels. These artifacts result from heart's expansion and contraction activity. Pulse artifacts, with a frequency around 1.2Hz, can resemble EEG waveforms and are difficult to remove. On the other hand, electrocardiogram (ECG) measures the electrical signals produced by the heart and can be recorded alongside cerebral activity. ECG artifacts can be easily removed by utilizing the reference waveform.

2.2 Methods

Independent Component Analysis: Independent Component Analysis (ICA) is a computational method employed to separate a multivariate signal into distinct subcomponents that are statistically independent from one another. It was first introduced by Aapo Hyvärinen in his Ph.D. thesis in 1997 and popularized by Jean-Francois Cardoso and other researchers. The goal of ICA is to find a linear transformation that can separate a set of mixed signals into independent sources. This is achieved by identifying the sources' statistical properties, such as their non-Gaussian distribution, and using this information to derive an optimal transformation matrix. The resulting transformed signals can be used for various purposes, such as feature extraction, denoising, or classification [14].

Let the input EEG signal from N sensors be,

$$Y = [y1, y2, \dots, yN]\ T$$

Each EEG signal from channel c with a duration of t, is represented as a column vector.

$$yc = [y(1), y(2), \dots, y(t)].$$

Its goal is to discover a separate matrix U which satisfies,

$$S = UY$$

In order to mitigate artifacts, artifact-free sources S' are obtained by removing artifact vectors from S. The spatial location on the scalp associated with each source is determined by calculating the row vectors of the unmixing matrix U. This information can then be used to create topographic maps of the source components using appropriate montages [15].

Independent components are extracted from the original signals. The reconstruction process involves discarding independent components that contain artifacts. In a study conducted by Jung et al., an enhanced version of ICA was proposed for analysing EEG and EPR data. They successfully eliminated EEG artifacts and compared their findings with regression techniques [16].

ICA is a superior and flexible technique for separating EEG signals from artifacts compared to PCA, which is restricted to orthogonal transformations. In ICA, the source signals are mixed together in a random and instantaneous manner. It is important that the dimensions of the observation signal are equal to or greater than those of the source signal [13].

ICA assumes statistical independence among sources, which might not hold in all scenarios. If sources are not strictly independent or the mixing process is nonlinear, ICA might not effectively separate the sources. Artifacts such as muscle activity or electrode drifts might heavily influence low-frequency bands, and if these bands are excluded before ICA, the method might not access the relevant information necessary for effective artifact removal. This limitation underscores the need for careful consideration of preprocessing steps before applying ICA. Adjusting or revisiting the frequency filtering methods to ensure that critical artifact information is retained can enhance the effectiveness of subsequent ICA-based artifact removal. Figure 1 shows the general Pipeline for ICA used for cleaning EEG signals.

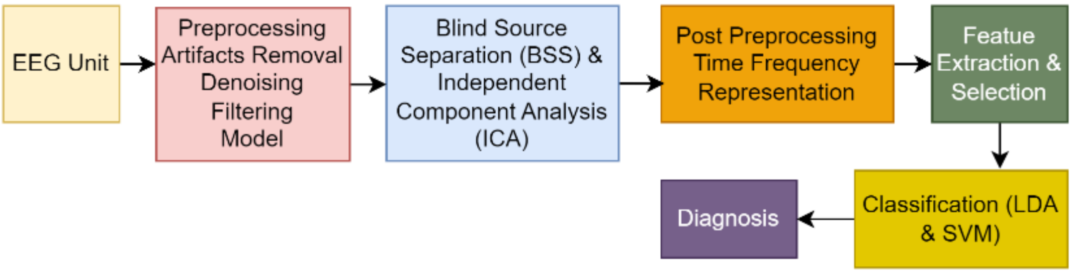

Figure 1. Independent Component Analysis

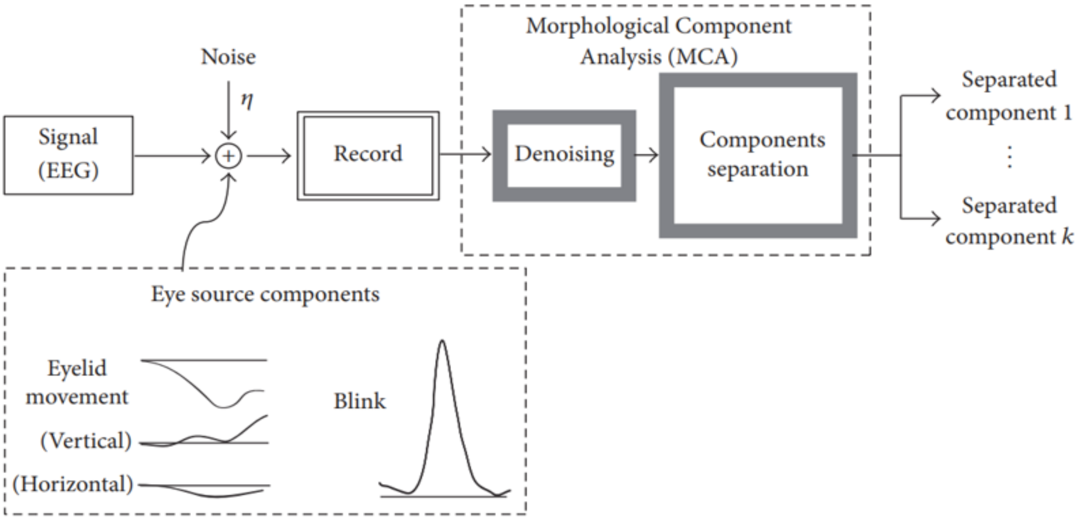

Figure 2. Morphological Component Analysis

Morphological Component Analysis: It is a mathematical framework for signal processing and data analysis that involves decomposing signals into their constituent morphological components [13]. MCA is particularly useful for analysing signals that contain both sparse and structured components. Figure 2 shows how these components are being separated to clean the EEG signal from the noise caused by the eye movements.

If a signal ‘S’ consists of individual components ‘S1, S2, ..., SN’ and each of these components is represented in a sparse manner using the basis ‘b1, b2, …., bN’ respectively, the signal S can be expressed as:

$$s = b1a1 + b2a2 + \cdots + bNaN$$

The signal S can be represented as linear combination of its components, ‘S1, S2, ... , SN’ using projection coefficients ‘a1, a2, ..., aN’. The components are represented sparsely with respect to the basis ‘b1, b2, ..., bN’. In this context, we consider a scenario where the signal ‘S’ (Raw EEG signal) is composed of two components, namely ‘s1’ (cleaned EEG signal) and ‘s2’ (the eye blink signal). It is crucial for the assumption of MCA (sparse coding) to hold that the dictionary of biases ‘b1, b2’ exists, such that each component in s is sparse in ‘b1’, and not as sparse in ‘b2’ [17].

Basic idea behind MCA is to represent a signal as a sum of morphological components, each of which has a specific shape or morphology [18]. These components can be thought of as building blocks that make up the signal. MCA seeks to identify these components and their corresponding coefficients by solving an optimization problem [19].

The optimization problem that MCA solves involves finding the sparsest representation of the signal in terms of the morphological components This objective is accomplished by minimizing the L1 norm of the coefficients while ensuring that the signal is decomposed into a combination of the morphological components, as specified by a given constraint [20]. The optimization problem can be solved using a variety of algorithms, including convex optimization techniques and greedy algorithms.

MCA assumes that EEG signals are a linear combination of independent components, and deviations from this assumption can impact its efficacy. Additionally, MCA assumes stationarity of signals over time, which may not hold true in dynamic EEG scenarios. The method requires independence between components and assumes linearity in signal mixing. On the computational front, MCA can be intensive, particularly with numerous EEG channels, posing challenges for real-time applications. Furthermore, parameter tuning is critical and time-consuming.

Principal Component Analysis: It is a statistical technique used to retain most of the information of the dataset while reducing its dimension [21]. The principal components are found by calculating the eigenvectors of the covariance matrix of the data, which are then sorted based on their corresponding eigenvalues, with the highest eigenvalue representing the most significant source of variability. The resulting components are orthogonal and uncorrelated, meaning that they are linearly independent from each other. Figure 3 shows that all principle components are orthogonal to each other. Also, PCA1 best represents the spread of the data.

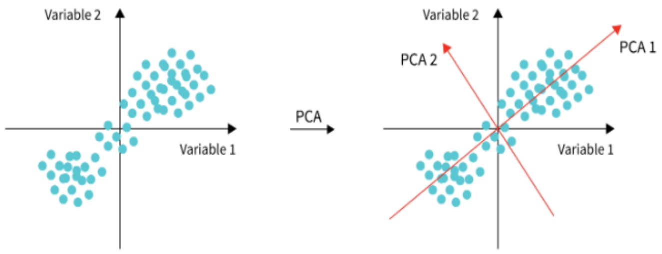

Figure 3. All of the principle components are orthogonal to each other

The assumptions used to approach PCA for optimum productivity include:

- Linearity: it is assumed that the principal components (PCs) are formed by combining the original features in a linear manner. If this assumption is violated, PCA may not yield the anticipated outcomes or may not be suitable for the given data.
- Large variance implies more structure: In PCA, variance plays a crucial role as it serves as a measure of the importance or significance of a specific dimension. Therefore, when applying PCA, dimensions with high variance are more likely to be selected as principal components.
- Orthogonality: In PCA, the principal components are assumed to be orthogonal to each other.

To use PCA for artifact removal in EEG signals, we can apply this equation to the data matrix X, where each row represents a time point and each column represents a different electrode [22]. The resulting U matrix contains the principal components, which represent the major sources of variation in the data.

To remove artifacts, we can identify the principal components that correspond to the sources of variability we want to remove, such as eye blinks or muscle activity. We can then reconstruct the original data matrix 'X' by selecting only the principal components that correspond to neural activity and multiplying them by their corresponding coefficients [23]. The resulting reconstructed data matrix 'X'' can then be used for further analysis or visualization.

PCA assumes linear relationships between variables in the data. However, EEG signals often contain nonlinear interactions that PCA might not fully capture. Complex nonlinear artifacts might not be effectively removed by PCA alone. It focuses on capturing variance as a measure of significance. However, this might not always correspond to the most relevant features for artifact identification and removal. Removing components based solely on variance might lead to discarding relevant information. principal components are orthogonal to each other. While this simplifies the computation, it might not accurately represent the complex relationships present in EEG data where different sources might not be strictly orthogonal.

Wavelet Convolution: The analysis of time-frequency was performed by utilizing the Continuous Morlet Wavelet Convolution (CMW) technique alongside the Fast Fourier Transform (FFT) algorithm. The procedure entailed converting the original data into the frequency domain using FFT, creating complex Morlet wavelets corresponding to each frequency, computing dot products between the wavelets and the FFT of the data, and then converting the outcomes back into the time domain using inverse FFT. Figure 4 shows the general pipeline used to clean input EEG signals using wavelet convolution.

This enabled the observation of variations in power over time. To demonstrate changes in power over time, the dot product results were converted back into the time domain using inverse FFT as follows:

$$T_x = IFFT\big(fft(C) \cdot fft(M_x)\big)$$

In the equation, 'T' represents a time-series data for a specific channel that has been filtered using a wavelet at frequency 'x'. The time-series data for all trials along with different phases is represented by 'C', and 'M' represents the complex Morlet wavelet at a specific frequency [24].

A wavelet can be thought of as a kernel in 1 dimension. They are like a sin wave which are tapered to 0 at the ends. We move the wavelet across the entire signal, and at each time point, we multiply the wavelet by the signal. The resulting product represents a coefficient for that wavelet scale at that specific time. We then adjust the wavelet and repeat the process [25].

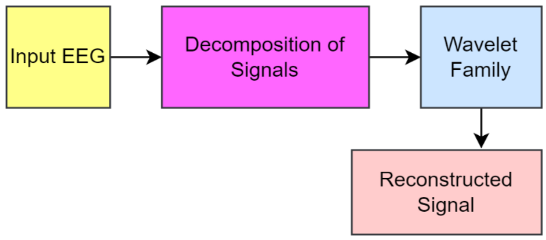

Figure 4. General pipeline for wavelet convolution

All waves can be thought of as time-frequency representations. The wavelet transform is used to do spectral analysis on various signals. In signal analysis using WT, it is crucial to select the wavelet and number of decomposition stages. This selection is based on retaining the portions of the signal that contain relevant frequencies for signal classification.

The transformation involves selecting time shifts 'k' and subsets 'j' of the wavelet 'I(t)', mathematically expressed as,

$$I_{k,j}(t) = \sqrt{2}I(2^j t - k)$$

then the wavelet 'W' can be done by,

$$W_I = \langle f, Ij, k \rangle$$

After decomposition of the raw EEG data with the help of wavelet transformation, components which do contain the artifacts are removed by setting a threshold. The artifact free signals can be regenerated using the remaining signal [26].

limitations include signal dependency and the potential loss of relevant neural information. Assumptions of stationarity and artifact separability are required, and computational complexity, especially for large datasets, can be a challenge for real-time processing.

3. CONCLUSION AND FUTURE WORK

The aim of this review is to offer a concise examination of the techniques employed for removing these artifacts. This review discusses several approaches, like Independent Component Analysis (ICA), Morphological Component Analysis (MCA), Principal Component Analysis (PCA), and Wavelet Convolution. Each approach offers unique advantages and challenges.

ICA allows for the separation of mixed signals into statistically independent subcomponents, aiding in the removal of artifacts. MCA, on the other hand, focuses on decomposing signals into their morphological components, making it effective for analysing signals with sparse and structured components. PCA reduces the dimensionality of the data while preserving variability, making it suitable for artifact removal by selecting principal components related to neural activity. Wavelet convolution enables time-frequency analysis, multiresolution analysis, and adaptive filtering, facilitating precise localization and removal of artifacts.

Artifact removal techniques such as PCA, ICA, MCA, and wavelet convolution are employed in EEG data processing, each with distinct advantages and challenges. PCA may overlook low-amplitude artifacts, ICA assumes statistical independence of components, MCA extends ICA with additional constraints, and wavelet convolution may struggle with non-stationary artifacts. Common assumptions involve the accurate representation of neural activity and source independence. Computational complexities vary, with PCA involving eigenvalue decomposition, ICA requiring matrix factorization, and MCA's complexity depending on imposed constraints. The suitability of each method depends on the specific EEG data characteristics, necessitating careful consideration of limitations, assumptions, and computational demands in choosing an appropriate approach for artifact removal.

Combining these techniques in a hybrid approach could leverage the strengths of each method while mitigating their individual limitations. For instance, a multi-stage process that uses PCA for initial artifact identification, followed by ICA for source separation, and MCA for refined artifact removal, may enhance overall effectiveness. Additionally, parameter tuning within each method, such as adjusting threshold values or refining constraints, could optimize performance based on specific dataset characteristics. Machine learning approaches, such as incorporating neural networks or deep learning architectures, could also be explored to adaptively learn and improve artifact removal. The dynamic adjustment of parameters based on real-time feedback or adaptive algorithms might further enhance the adaptability of these methods to diverse EEG datasets.

The development of machine learning, deep learning, and statistical approaches has contributed to the advancement of artifact removal methods, enabling researchers to tackle various types of artifacts originating from environmental noise, experimental errors, and physiological sources. These methods not only enhance the reliability and quality of EEG data but also streamline the research process, enabling researchers to extract meaningful information and contribute to the advancement of neuroscience and its applications. With further advancements and refinement of these techniques, the field of BCI and EEG research will continue to progress, offering new possibilities and insights into brain function and its potential applications.

Advancements in EEG artifact removal have broad implications, improving diagnostic accuracy in healthcare, enhancing signal reliability in brain-computer interfaces, and refining cognitive neuroscience research. The technology also benefits human-computer interaction, impacting mental workload assessment, driver fatigue detection, and adaptive learning systems. Moreover, it plays a crucial role in affective computing applications, influencing emotion recognition in virtual reality, gaming, and human-robot interaction. Overall, progress in this field contributes significantly to healthcare, neuroscience, and the efficacy of human-machine interfaces.

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