Methods for removal of artifacts from EEG signal: A review

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Abstract. Electroencephalogram (EEG) is the record of cerebral activity, the electric potential of cerebral activity is of low amplitude, and less frequency ranges between 4 to 60 Hz, which can easily mix up different non-cerebral signals and other environmental noise signals. The extraction of actual cerebral signals from the contaminated EEG signal is the major challenge in medical analysis. Somehow, during the recording of the EEG signal, contamination of other signals takes place, which increases complexity in analyzing the accurate EEG signal. This leads to inaccurate information signals in the analysis. Accordingly, the process to eliminate the unwanted signals in the pre-processing level is mandatory in brain signal analysis. The unwanted signals from various sources are together termed as artifacts; the researchers have implemented various techniques to reduce the undesired signals. However, still, there is no standard technique in detecting and eliminating the artifacts, and hence, the research became most challenging.

Keywords: Discrete wavelet transform (DWT), Empirical mode decomposition (EMD), Independent component analysis (ICA), Canonical correlation analysis (CCA), Singular value decomposition (SVD),

1. Introduction
The Electroencephalogram (EEG) represents states of the brain of the human being’s mental condition. EEG signals are the electrical potentials of the cerebral, which is contaminated with other bio-potentials like Electrocuculogram (EOG), Electrocardiogram (ECG), and Electromyogram (EMG). Hence the segregation of EEG signals from different bio-potentials is a challenging task for analyzing EEG signals. Source separation methods focused much attention on EEG signal analysis; primarily, the source separation techniques are designed based on two types of artifacts; they are extrinsic and intrinsic artifacts [1-3]. Extrinsic artifacts have occurred electric and electronic components, namely high electrode impedance and meddling, line noise, earthing problems, electrode failure, ventilation, and power supply. Intrinsic means various artifacts that occurred in EEG signals like movements of the eye, eye blinks, bioelectric potentials from muscle, heart etc. Artifacts are unwanted components that arise from other sources; they mislead the actual cerebral activity of present recorded EEG data, and hence this leads to more complex in analyzing the EEG data. Due to artifacts, the accurate EEG signal is misguided. Hence the extraction of original EEG signals from contaminated EEG signals occupied the highest priority in the field of EEG signal processing.

In the last thirty years, the EEG machines have gained great significance due to low power consumption. Several techniques were implemented by the researchers for eliminating artifacts. This review paper will provide a record of a detailed overview of distinguished methods to minimize and eliminate the artifacts in EEG signals. The first remedy to deduct artifacts in the EEG signal is to avoid movements that can incur them. Several methods have been implemented to reduce the
artifacts; however, the investigation on reducing the several undesired components remained to be a prevalent problem.

2. Background

In 1875, Richard Caton exposed the brains of rabbits and monkeys. Later in 1875, Adrian and Matthews verified perception on “Human brainwaves” recognized standard electrical bio-potential ranges between 10-12 Hz and named as “Alpha Waves.” EEG is the average sum of ionic current, this current which flows during the synaptic excitations of the dendrites in a neural ensemble of the cerebral cortex. EEG measures the action of many neurons. Hans Berger traced the signals by recording through the EEG machine in 1929 for the first time. The human brain is divided into five different lobes named as the frontal lobe, parietal lobe, occipital lobe, temporal lobe, and cerebellum. These lobes are the origins of the various electrical potential that are generated based on human activities. As the electrical field produced by the neural activation travels, its voltage decreases and with every barrier (Dura mater, skull, skin) between the cortex and scalp, which are recorded as electroencephalogram and shortly known as EEG (Figure 1).

![Figure 1. Elements of Human Brain.](image)

The EEG recording process is non-invasive, trouble-free, and does not create pain for the patient. EEG recordings resemble the global behavior of the brain. These waveforms display the rhythmic pattern at characteristic frequencies. EEG signals associated with the behavior of human activities such as excited, relaxed, drowsy, asleep, deep sleep, coma etc. These activities fall into distinct rhythms of frequency ranges, as shown in Table 1.

| Type   | Frequency     | Activity         | Location                  |
|--------|---------------|------------------|---------------------------|
| Gamma  | 20 – 60Hz     | Visual attention | Occipital                 |
| Beta   | 14 - 20 Hz    | Mental activity  | Parietal and frontal      |
| Alpha  | 8 - 13 Hz     | Sensory stimulation | Occipital and parietal  |
| Theta  | 4- 8 Hz       | Emotional Stress | Temporal and parietal     |
| Delta  | Less than 4 Hz| Occur during sleep, coma | Everywhere          |
2.1 Types of artifacts
In pre-processing of EEG data identifying the artifacts has the highest priority. The artifacts corrupt the originality of EEG data. In this regard, the artifacts are requisite to get rid of actively. The cardiac Artifacts, muscle Artifacts, ocular Artifacts, and external device Artifacts are the typical artifacts that intermingle with EEG signals (Figure 2).

![Diagram of EEG signal components](image)

**Figure 2.** Various Bio-Potential Artifacts.

2.1.1. Cardiac Artifacts
The pulsating human heart generates the electric potentials known electrocardiogram. These electric potentials of the heart (ECG signals) are conducted to the scalp, which is intermingled with the EEG signals, thereby creates the potential change in the measured signal of EEG Cardiac artifacts are of two types Mechanical and Electrical. Every contraction and irregular interval of cardiac arrhythmia can be considered as mechanical artifacts. The electrical artifacts may be due to the heart electrodes. ECG artifacts may disrupt the EEG background activity that which is the replica of epileptiform discharges. Moreover, it usually is diphonic or triphonic with an active component that has duration within the spike range. Cardiac artifacts are of two types Mechanical and Electrical. Every contraction and irregular interval of cardiac arrhythmia can be considered as mechanical artifacts. The electrical artifacts may be due to the heart electrodes.

2.1.2. Muscle Artifacts
EMG has a broad classification from 0Hz to >200Hz [1, 4]. EMG is the muscle activity potential that is generated at various muscle groups; the EEG signal that is measured consists of EMG potential that contaminates the original EEG signal [5, 6]. Moreover, EMG has an effect on both temporally and spatially.
2.1.3. Electrode Artifacts
EEG measurement consists of apparatus, equipment, and connections. Most probably electrode artifact, and may occur due to Amplifier artifact, Capacitive artifact, Inductive artifact, Electrostatic artifact, aliasing artifact. Poor Contact of the electrode may affect the electrode impedance, which results in low-frequency artifacts. Temperature variations and biasing error in instrumentation amplifiers may cause due to the baseline drift. More problems with electrode artifact results in prolonged monitoring and scalp integrity.

3. Traditional Methods in Artifacts Removal
3.1 Regression Method.
The fundamental process for eliminating unwanted signals in EEG is the regression method [7]. This method described the amplitude relation of reference and estimated artifacts from EEG; Thereby, this algorithm requires external reference signals such as ECG, EOG, and EMG to segregate the various undesired signals. From figure 3, the first stage output consists of EEG, ECG, EOG signals, where line frequency is omitted with reference channel as a linear filter; finally, the corrected EEG data can be obtained (Figure 3).

\[ e_3(n) = e_2(n) - e_1(n) \]

Figure 3. Regression method approach.

Hillyard and Gallambos, [8] done their research in removing EOG based on the time-domain regression approach. Whitton et al. [9] approached based on frequency domain regression, and in conjunction with the software tool, the EEG signal had been analyzed. Where ocular potentials can contaminate the EEG potentials and similarly. The simplified model and reduced computational method are the pros, and it needs the reference channels for eliminating the EOG, and ECG remained as cons of the regression methods [1]. The researchers found the counterclaim to a regression algorithm named Blind source separation techniques, but still, the regression methods remained as a golden foundation to appraise the novel approaches.
3.2 Wavelet Transform

All waves may be considered forms of time-frequency representation. The spectral analysis of various signals is performed using the wavelet transform. Choosing the appropriate wavelet and the number of decomposition levels is very significant in the study of signals in WT. Wavelet decomposing of levels is based on the frequency domain of the signal [10-12]. The levels are selected such that those parts of the signal that associate well with the frequencies required for classification of the signal is retained in the wavelet coefficients. Finally, the transformation is achieved by the selection of subsets ‘j’, and time shifts ‘k’ of the mother wavelet $\Psi(t)$. where ‘j’ and ‘k’ are integers. Therefore, mathematically expressed as:

$$Y_{j,k}(t) = 2^{j/2} \Psi (2^{j} t - k)$$

Now, the wavelet can be performed by:

$$W_f = <f, Y_{j,k}>$$

![Figure 4. Block Diagram of Wavelet Transform System.](image)

From the figure 4, the input signal is raw EEG signal, in the next stage it is decomposed into various levels, Discrete Wavelet Transform is the result of continuous wavelet can be applied when the input signal and the decomposition can be expressed as:

$$X_a, L[n] = \sum_{k=1}^{N} X_{a-1} \cdot L[2n-k] \cdot g[k]$$

$$X_a, H[n] = \sum_{k=1}^{N} X_{a-1} \cdot L[2n-k] \cdot h[k]$$

$g[n]$–low frequency component of low pass filter.

$h[n]$- high frequency component of high pass filter.

After decomposing wavelet transformation on EEG data, then the threshold is chosen to reject that component, which consists of artifacts. Now with the leftover, the signal is reconstructed without artifact. In the process of artifact deduction, the DWT was declined to categorize artifacts. However, still, the DWT approach must move forward on artifact attenuation that has common characteristics with the spectral properties; for this reason, new work carried out by the mixture of DWT with new methods similar to ICA.

3.3 Blind Source Separation
BSS technique had the superior flexibility with a multiplicity of learning algorithms such that no extra reference channels and any preliminary information. Assume that X be an electric potential signal generated by EEG electrodes. Moreover, S is the source signal (original and artifact signal). The source signal is mixed with an unknown matrix A then,

\[ X = AS \]  \hspace{1cm} (6)

To obtain the observed signals BSS algorithm is an extended version:

\[ U = WX \]  \hspace{1cm} (7)

Where U is the assessment of sources and the W is the reverse mixing of X. Subsequently, the components as artifacts are removed, and then with the remaining components, the EEG data is reconstructed. Some representative works that have adopted from BSS are discussed below.

3.3.1 Principal Component Analysis
PCA is the most widely used tool for investigative data analysis and for making predictive models. It is a static process to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components [13-16]. Berg and Scherg, [17] work proved that the ocular artifacts could be removed. In this effort, the extraction of EEG data was obtained by eliminating the blinks and eye movements. Therefore, the accurate EEG signal is obtained. PCA algorithm failed in segregation, where the potentials of drifts and EEG potentials are similar. As a result, later research prefers further flexible methods.

3.3.2 Independent Component Analysis
ICA is a part of BSS, in its unique way. A typical example application is the ‘cocktails party’ problem of listening in one person’s speech in a noisy room. In EEG signal analysis, signal sources are direct mixtures of cerebral and other different sources, that can be decomposed into independent components ICs [18]. The Independent components are extracted from the raw original signals. Now the reconstruction is implemented by rejecting the ICs components that contain artifacts (Figure 5). To analyze the EEG and EPR signals, the extended version of ICA is proposed, Jung et al. [19] succeeded in removing the EEG artifacts and judging the results against regression methods [20].

3.3.3 Canonical Correlation Analysis

The expansion of PCA confined to transform orthogonal directions; ICA provided the evidence in source signal separation in a more effective way. ICA approaches introduced by several researchers in the extraction of signals from various mixtures and to decrease the artifacts of different sleep stages. ICA can calculate approximately the original signals which are non-Gaussian.

Figure 5. Block Diagram of Independent components Analysis Method.

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3.3.3 Canonical Correlation Analysis
Most prevalently and effectively used signal processing technique as that is evolved from BSS is Canonical correlation analysis (CCA). CCA has variation from ICA in its concept in separating the components and has less computation time, which is the advantage of ICA. By comparing the CCA and ICA, CCA, with the correlation of signals, declared that both have similar qualitative results, but differ in computational complexity. In contrast, ICA considers the statistical distribution of the same samples into account. Correctly, the CCA was implemented to remove muscle artifacts from EEG [21]. The author explored the dissimilarity over brain and muscle artifacts, and finally, the components with the least autocorrelation were choosing to reject.

3.4. Empirical Mode Decomposition

EMD method is a practical and data-driven technique, whereas other methods depend on the selections of essential functions, such as wavelet analysis [18]. Let the signal x(n) it can be decomposed as a linear combination of finite number (N)bk(n) and residual r(n). A shifting process is done to calculate the IMF of the given signals, at the end the original signal is constructed as,

\[ x[n] = \sum_{k=1}^{N} b_k(n) + r(n) \]  

EMD algorithm has one negative aspect of that the sensitivity of noise, which incurring mode mixing complications, that the sensitivity of noise [22]. Another tailored EMD, to decompose multivariate signals into multivariate IMFs. Therefore, the simultaneous analysis of intrinsic modes across multiple channels, i.e., Multiple Empirical Mode decompositions, can more efficiently and accurately remove artifacts related to broadband muscle artifacts.

3.5 Filtering Methods

In eliminating the artifacts, several filtering methods play a vital role in EEG analysis. Most basic filtering methods are adaptive and wiener filtering methods. This paper, in brief, illustrates the commonly used filtering approaches.

3.5.1 Adaptive Filtering

An illustration of the adaptive filter is as followed in figure 6. At the input stage, the primary input. The primary input is a combination of both real EEG data and an artifact source, and expressed as:

\[ EEG_{pri}(n) = EEG_{pure}(n) + N(n) \]  

![Figure 6. Adaptive Filter System.](image)

Where, EEGpri represent the primary signal, EEGpure represent the pure signal. 'N' is the noise signal, which is a mixture of various artifacts. Another input to the filter is given to the reference channel. To examine the pure signal, EEGpure, the least mean square, is used. As an extension to LSM, the recursive least mean square (RLMS) is implemented, which is faster than LSM, but the drawback is high calculation cost due to additional sensors to provide reference inputs [23].

3.5.2. Wiener Filtering
In signal processing, the wiener filter solves the signal estimation problem. It is capable of estimating the target process by time-invariant filtering of an observed noisy signal process of presumptuous stationery and noise spectra. However, it is a statistical filtering method to examine and inspect the true EEG data, employs a linear invariant filter to minimize the mean square error between the pure EEG signal and estimated signal [24]. However, the limitation of extra reference channels overcome by wiener filter but a bit complex in computation.

4. Hybrid Methods
To avail the benefit from established approaches, novel research approaches came into the scenario, the conjunction of various methods known as hybrid methods, which means a combination of two or more methods [25-27]. The fundamental hybrid strategies are discussed below.

![Figure 7. Process flow of the EMD-BSS method.](image)

Figure 7 represents the process flow of the EMD-BSS method, in which the raw contaminated EEG data is decomposed by the EMD algorithm, combined with BSS to remove artifacts and to reconstruct the clean EEG by applying the reverse algorithms. This hybrid method is the most powerful tool in the removal of EMG artifacts from EEG signals; other side complexity is more in computing and identifying the artifactual components.

4.1. Wavelet -BSS
Whilst WT failed, in the case, if the artifacts overlap with the spectral properties in the spectral domain, this remained as the limitation of ICA, the conjunction of ICA with wavelet method has been proposed to avoid the short comes of both and to pick the positive [28-31].

![Figure 8. Block diagram of Wavelet –BSS Method.](image)

Figure 8 shows the block diagram of the Wavelet-BSS method. Initially, the EEG signal data is decomposed with WT, and EEG data is decomposed by WT, and then contaminated data components are fed into the selected ICA algorithm. However, at the endpoint, artifacts are removed and reconstructed using preserved wavelet components and disposed components.

4.2. BSS and Support Vector Machine
A further extended method of BSS in the hybrid model is BSS-SVM. Using BSS, the recorded raw EEG data were decomposed into multiple components. In the subsequent level, extraction of numerous features takes place such as temporal, spatial etc. Then the extracted features are given as input to SVM classifier to examine the artifacts and to reconstruct the signal with the remaining
components as artifact-free signals. Figure 9 shows a schematic of the BSS-SVM method. Shocker et al. [32] first applied BSS with SVM to eliminate artifacts related to eye blinking.

![Figure 9. Block diagram of BSS –SVM Method.](image)

5. Comparative Analysis

The different methodologies summarized in this paper are most widely used, removing the artifacts of the EEG signal. Few techniques implemented to remove eye blinking and eye movement’s artifacts. The majority of EEG related applications are real-time applications like bio medical-signal processing can be booming with the help of the reference signal. Regression and filtering algorithms can be efficiently executed to eliminate the various artifacts. Filter methods have more practically opted methods for specific reference artifacts. The requirement of the reference channel that detains the adaptive and regression algorithms in removal of the unsurpassed artifacts. WT transforms not make the grade to identify artifacts that overlap with spectral properties. BSS techniques ensure flexibility because it does not require any preceding data and extra reference channels.

Along with these BSS methods, ICA the separation is done, where the signal is converted into independent components as ICs with the decomposing process, and by discarding the artifacts, the new signal is reconstructed. In CCA algorithm was implemented to separate the EMG potential from EEG potential, and the computational time is less. Due to this CCA algorithm is applicable in real-time application. In such circumstances, the BSS is not suitable due to which it works on a more significant number of channels, and the accuracy in obtaining the truth is high. Zou et al. [33] following the ICA algorithm was extended by a grouping of ICs components; therefore, physiological and non-physiological artifacts are identified from the EEG signal data. BSS method is incorporated with advantages of both ICA and CCA into one single carcass vector analysis, which is used to reject the muscle artifact by extracting the sources with maximal independence and maximal autocorrelation [34, 35]. Contrasting the convention algorithms, machine learning-based approaches became new research projections to identify artifacts using massive datasets.

6. Conclusion

EEG potentials are originated from the cerebral cortex, which is picked up with scalp electrodes. EEG signals, however, continuously merge with unwanted surrounding signals. In fact, a wide variety of techniques have been implemented to remove the undesired signal components known as artifacts, and these artifact removal methods still require high accuracy and efficiency. This review paper recaps the basic approaches and conclusions set by the researcher’s literature. The pros and cons are emphasized for each method. Consequently, there is no most excellent preference method for removing of all categories artifacts. As a result, the main focused future objective is to implement a specific algorithm for sufficient attenuation of artifacts with better accuracy and efficiency.

In conclusion, there is a future scope where machine learning and traditional methods may combine to develop new distinguished algorithms to achieve an effective removal of artifacts in EEG signal analysis.

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