



Updates on Electroencephalogram (EEG) Denoising Techniques

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ABSTRACT

Electroencephalogram (EEG) is an electrical signal which depicts brain activities; it is collected to analyse and study the brain activities from the scalps using electrodes. Several unwanted components called artifacts or noise contaminate the desired EEG signal during the raw signal collection. These components include eye blinking, environmental factors, power source, muscle movements, and heart rate affecting EEG processing and analysis. Therefore, it is necessary to eliminate or reduce these components in a process called EEG Denoising. Several denoising techniques have been proposed by researchers. This paper review these techniques and works carried out by researchers in that direction from the last decade to the present. This study also highlights the theoretical aspect of EEG signals. Findings reveal that there are still some drawbacks with conventional denoising techniques, such as the inability to denoise certain types of noise and loss of desired information resulting from discarding the unwanted components. In recent times, researchers have been combining conventional techniques with other modern techniques such as machine learning to improve their algorithm's performance. Machine learning and deep learning techniques are a new trend in EEG denoising, which provides high performance and efficiency with an automated solution. From the analyses conducted on various articles reviewed in this study, comparative analysis with the advantage and disadvantages of each method have been highlighted and discussed with some recommendations for selecting a suitable technique based on a particular application and scenario.

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INTRODUCTION

Electroencephalogram (EEG) is a human brain signal that records a neuron's electrical activity using various scalp-mounted electrodes [1]. The EEG signals dynamics changes with physical conditions and cerebral activities, an example of such activities includes conducting speech imagery tasks, motor imagery, activation to any stimuli while relaxing, or being in pathological state and healthy state [2]. In clinical setup, EEG has a wide range of applications in different areas. It is a valuable signal used as a diagnostic tool in the early detection of epileptic seizures [3-4], dementia-related disorders [5,6], stroke, autism, sleep disorders, and mental state

monitoring [7-10]. Besides, EEG finds further applications in designing various neural prosthetic devices and Brain-Computer Interface (BCI) systems [11].

Prosthetics devices such as a wheelchair, robotic arm, and other assistive devices can now be controlled by physically challenged persons to enable them to perform various tasks [12]. The BCI system is an emergent field in EEG research that provides an alternative path for interaction between the external world and the brain through a computer. It uses brain signals, and analyses brain mental activities to command a machine in assistive applications such as the new communication method for

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patients of Amyotrophic Lateral Sclerosis (ALS), neuromuscular disabilities, paralysed patients, among others [13].

EEG generated by the cortical section of the brain is termed as Physiological artifacts. It may include some contaminated elements by non-cerebral artifact origins [14], such as Electrocardiogram (ECG) artifacts generated by heartbeats, ocular artifacts (EOG) by eye blinks, and Electromyogram (EMG) artifacts like tongue, jaws movements [15]. Other artifacts that affect

EEG acquisition are technically induced artifacts caused by faulty electrodes, high electrode impedance, line noise, and interference from equipment and devices [16]. Generally, EEG-related artifacts can be categorised into two groups; those generated internally from the human body (biological activities), termed as interior artifacts and those with external sources referred to as exterior artifacts (summarised in Table 1).

Table 1: Type of artifacts in EEG signal

Interior Artifacts	Exterior Artifacts
Blinking of the eye (EOG.)	Power line
Heartbeat (ECG.)	Machine fault
Muscle movements (EMG.)	Faulty Electrode/Poor Placement
Skin resistance	Ventilation
Subject's Movement	Digital Artifacts (e.g. Loose Wiring)

These unwanted components severely reduced the signal's quality and diminished the accuracy of further processing like feature extraction and classification. The effect of reduction in system accuracy can be seen in the change in event-related potential signals in the BCI system, which may lead to erroneous control of the device, decreased recognition rate in epilepsy detection and classification, sleep disorder, Alzheimer's disease, vascular dementia, autism spectral disorder studies, depression among other neurological disorders. Therefore, the need for denoising and removal of these artifacts and noises can never be over emphasised. Different techniques and algorithms have been developed over the years to eliminate the artifact and noise from EEG signals to make them more reliable for further processing and analysis [16-17].

Among these denoising methods includes early prevention steps taken during the EEG recording, which includes preventing muscular and ocular artifacts by limiting eye blinking, eye movements, and movements by other parts of the body. Another method is by threshold criterion, excluding corrupted trials of EEG signals recording [18]. The method of locating and eliminating contaminated activity is

also feasible using Electrooculogram (EOG) subtraction technique [19]. Independent Component Analysis is one of the most popular techniques in EEG artifact rejection and denoising. In recent times, time-frequency techniques have been extensively studied by researchers as a viable approach that includes wavelet transforms denoising techniques.

Researches also proposed statistical approaches and other stand-alone EEG artifacts elimination techniques, conventional filtering, artifact cancellation using combined reference signals, and adaptive filtering. Over the decade, many algorithms have been developed that combine time-frequency and statistical techniques and other techniques to improve artifact rejection in EEG signals. The chart in Fig. 1 provides the percentage of each method observed in our reviewed articles.

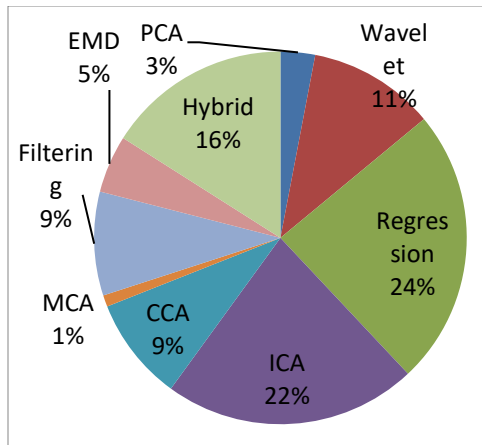


Fig. 1. Percentage of different methods used in the reviewed articles

Due to different characteristics and sources of artifacts, many studies have focused on removing a single type of artifact, but some researchers have focused their study on eliminating the different types of noise and artifacts. Other improvements witnessed recently include using suitable and effective performance measures and automated algorithms. However, to date, it is difficult to identify a single method that eliminates the artifacts without distorting the original EEG signal whatsoever. This review provides a comprehensive literature survey of recent techniques that have been used for artifact cancellation and denoising of EEG signals. Their advantages and limitations are also presented.

Performance of the various algorithms is evaluated using validated metrics; the most commonly used metrics have been highlighted and analysed. Finally, suggestions were given on some challenges, future direction, practical implementation, industrial and clinical applications of EEG signal and noise separation elimination research. To ensure a detailed and comprehensive review of EEG denoising related works for various applications, Google Scholar, Science Citation Expanded, Scopus, EI Compendex, and other search engines and journals were used in our search. The key terms used are 'EEG denoising', 'EEG artifact removal or rejection,' and 'correction.'

From our survey, 34% of the reviewed articles covered muscle artifacts rejection. This artifact is essential and unavoidable since the ambulatory health care system is increasingly employed and adopted. Hence, such EMG artifacts are given much attention in recent days. Ocular artifacts also covered 28% of reviewed articles, while 15% covered artifacts that are related to heartbeat. Fig. 2 shows in percentage frequency of study of each type of artifact covered in our reviewed articles.

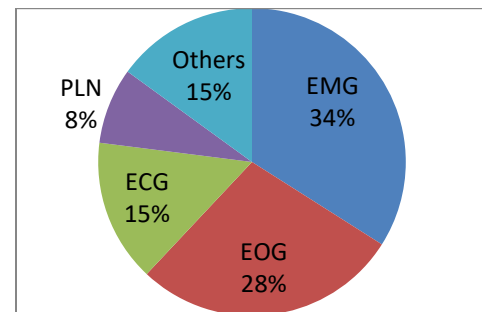


Fig. 2. Percentage frequency of artifact type covered in the review articles

This paper also contributes to the research community by helping researchers who may want to develop efficient noise elimination methods in their EEG signals related applications and those who want to develop new methods to improve the existing approaches.

THEORETICAL CONSIDERATION

In this section, we discussed some of the related theoretical concepts about the EEG signal.

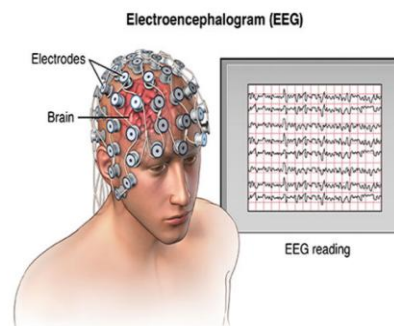


Fig. 3. An illustration of EEG recording [10]

EEG Signal

Fig. 3 shows how the EEG is recorded noninvasively using electrodes placed on the scalp with signals displayed on a computer. This signal depicts the electrical activity of the brain as the electrodes pick up electrical charges. However, invasive electrodes can be used in some applications, known as intracranial EEG (iEEG). These electrical recordings from the brain's surface and even from the outer surface of the head revealed that there is continuous electrical activity in the brain [20].

Based on the state of the brain, the frequencies and amplitudes of the brain signal (EEG characteristics) change in the event of activities such as sleep, wakefulness, disease state like dementia, epilepsy, sleep disorder, and the mental state. Fig. 4 depicts an example of a typical EEG signal, while Fig. 5 depicts EEG recordings with four types of common artifacts in human EEG signals viz: 1. ocular artifacts 2. Electrode's artifact 3. Swallowing artifact and 4. Common reference electrodes artefact [21,22].

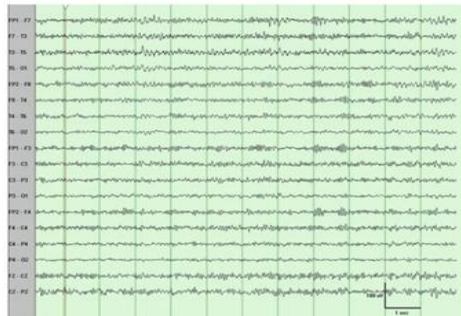


Fig. 4. Normal EEG signal

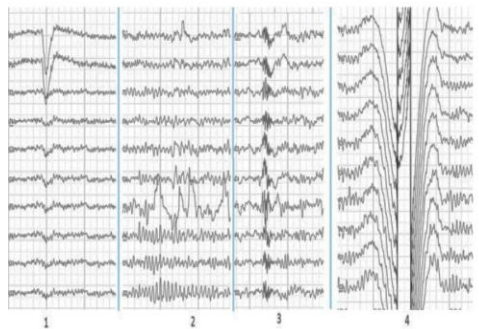


Fig. 5. EEG recordings with four types of commonly artifacts

Characteristics of EEG Signals

One of the most important scales in clinical EEGs for evaluating defects and in cognitive research is frequency. 0.01 Hz – 100 Hz range is the typical frequency range of a normal EEG signal. However, this frequency is grouped into five sub-bands: delta, theta, alpha, beta, and gamma [22]. Details on the frequencies associated with these bands are provided in Table 2.

Table 2: EEG Frequency Bands

Frequency Band Name	Frequency Bandwidth (Hz)
Delta	< 4
Theta	4 - 8
Alpha	8 - 12
Beta	12 - 30
Gamma	< 30

Artifacts Rejection Algorithms

This section presents an adequate study of literature on the most popular techniques used over the years to reject and eliminate or suppress artifacts in EEG signals. We also highlighted a brief theory of their concept, major steps in their operations, and limitations.

EEG. Early Prevention Steps

Early prevention steps are direct methods to reduce noise and artifacts in EEG measurement by preventing motions and movements that can cause them. The subjects can be asked to avoid unnecessary blinks, the eye's motion and stay still as much as possible without body movements. However, controlling certain parts of the body could be very difficult; for example, it is almost impossible for the subject to control his pulse. To control eye blinks and motion for a long time is almost impossible too. Therefore, we cannot rely on these steps alone for an EEG denoising solution, especially in other applications like BCI [23,24]. Other techniques must be employed to achieve real solutions.

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Threshold Criterion

The threshold criterion method is another early artifact rejection step to eliminate all epochs greatly affected by signals from technical sources [25]. However, to recognize artifactual epochs from large EEG data sets is very hard/computationally complex as it takes a lot of time and deep knowledge of EEG data analysis. Another drawback of this technique is the loss of some useful information present in rejected epochs which might cause inaccurate interpretation and conclusions. Therefore, using other automatic and advanced techniques would be preferable.

Blind Source Separation Techniques

Blind source separation techniques (BSS) are commonly used techniques for artifacts and noise removal from EEG data by excluding neuronal activity signal sources from artifacts sources [26]. One of the major merits of BSS is that the previous mixing information from different sources is not needed, or in some situations, a minimal amount of information is needed. Let X be multichannel EEG signals with linear mixing of sources S ; then from equation (1), X can be mathematically described as:

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

Where A is the mixing matrix.

BSS can be used to generate an un-mixing matrix W to separate the sources, as in equation (2)

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

Where \hat{S} is the estimation of the sources, and W is the demixing matrix.

Once all neuronal and artifactual sources are known, the latter can be removed to obtain artifact-free EEG. Fig. 6 shows the general schematic of artifact removal using BSS algorithms. There are many BSS algorithms developed to remove artifacts from EEG signals, including independent component analysis (ICA), principal component analysis (PCA), canonical correlation analysis (CCA), and morphological component analysis (MCA).

Independent Component Analysis

One of the popular and typical approaches in EEG artifact elimination is ICA. A multivariate analysis decomposes the original signals from various sources into a brand-new set of independent components (ICs). Generally, we can classify the identification of artifacts using ICA into three stages. 1. The signals can be decomposed into ICs. 2. Identified stand-alone ICs that are varied from each other and, in most cases, manually discarded and 3. Organised artifact-free signals by concatenating the remaining ICs [27]. In ICA, the signals are assumed to be linearly mixed from different sources and are independent. Some of the advantages of ICA over other methods such as adaptive filtering and other parametric techniques are: Efficiency depends on the statistical independence of the mixing matrix and the source of signals; even in situations where the artifacts sources and EEG sources are entirely independent, ICA proved to give a better result. Moreover, in ICA, it is unnecessary to require any additional reference channel or prior information for artifact rejection.

Custom software such as EEG Lab [28] and Brainstorm [29] have been used to detect and remove EEG artifacts and noise using the user's control based on the ICA approach. Some of the reported works in the literature using these software includes [30-31]. However, a direct rejection of the signals may result in the loss of some useful information in the signal. It is thus necessary to analyse and develop other techniques to improve the conventional ICA-based approach.

Several works have been reported in the literature to improve the conventional ICA-based approach, such as in Yin et al. [32] -The authors combine ICA algorithms with factor analysis (FA) and multivariate empirical mode decomposition (MEMD) to eliminate the undesired power of additive noise in the EEG signals. Two types of noise appeared; one is generated from each sensor as additive noise, and the other is common component noises. ICA approach cannot remove the additive noise, so factor analysis (FA) is employed initially to reduce the additive noise's

power. While ICA is employed to remove noise components by performing the independent source decomposition, FA and multivariate empirical mode decomposition (MEMD) were used to remove the unwanted power of additive noise in the EEG signals.

The study reported in [33] present a technique that reduces information loss in the signal using ICA with a regression approach. The ICA is employed initially to generate independent components (ICs) and identified artifactual ones; after that, mathematical regression ensures that only artifactual components are eliminated to avoid information loss. They achieved this by using a control feedback system to identify those artifacts from the residual artifacts components. This approach yielded improved results. Other works reported in the literature include Zamm et al. [34] which used CORRMAP EEG Lab plug-in written by Filipa Campos Viola with Hamming window finite impulse response (FIR) filter to prepare ICA. They applied the moving average filter to overcome the drawback of [35] after applying ICA.

However, to obtain a higher accuracy result with the ICA approach, provided the sources are reasonably spatially stationary, the amount of data to be used should be reasonably maximum.

ICA results primarily rely on the amount of data supplied to the algorithm. Hence, Atti et al. [36] proposed data of 10-sec duration; another author Winkler et al. [37], claims that many times the number of channels should be used as the sample size. The work of Amuse and Sobi is based on the minimisation of the correlation between signals and performs well with the data of short duration [38].

Despite ICA's promising performance, some precautions need to be taken into consideration. The consequences of the method on the neuronal part of the signal are mostly abandoned as most of the works on ICA concentrate extensively on eliminating the artifacts from EEG signals [38]. Moreover, choosing the components that contain the artifacts is highly dependent on the experimenter/researcher's experience because it is performed by visual observation of ICs time series and tomographic maps. Thus, this method resulted in obtaining different results. However, researchers recently developed methods for automatic artifactual components determination. Even though it does not address the loss of neuronal information, this technique is efficient in artifact reduction and computational cost [39].

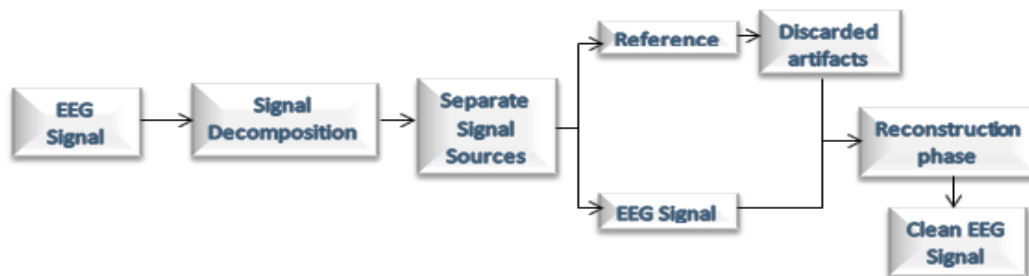


Fig 6: BSS general schematic of artifact removal

Another ICA drawback is the assumption that several signal sources must be equal to or less than the number of channels and cannot be used on a few or single channels. As a result, researchers have employed many efforts to modify and improve the ICA-based artifact removal, such as in [40].

Principal Component Analysis (PCA)

PCA is a mathematical procedure that can reduce the dimension of a large set of variables into a smaller set that retains most of the information contained in a large set. It transforms time-domain observations using the orthogonal transformation of possibly correlated variables into linearly uncorrelated ones called principal

components (PCs). In EEG measurement, the number of channels must be equal to or greater than the number of PCs.

If n is the number of observations while p is the number of variables, the number of PCs is given in equation (3) as:

$$\min(n - 1, p) \quad (3)$$

This transformation is designed so that the first PC has the highest possible variance, and each preceding PC has the lowest variance possible under the constraint of being orthogonal to the succeeding PC [41]. Different authors have reported several works using the PCA approach to eliminate artifacts from EEG data, such as in Gerla et al. [42], which determined the spatial distribution of eye activity. Lakshmi et al. [41] used PCA in removing artifacts from EEG signals. Although PCA has shown promising results than regression-based methods, as reported in Plöchl et al. [43], some drawbacks are associated with PCA. The major one is its orthogonality assumption that is not valid for artifacts and neuronal activity. The PCA cannot identify the artifacts components when the amplitude of artifactual activity is the same as that of the neuronal activity component. Many PCA improvements and extensions have been reported in the literature. However, ICA tends to be preferred [44].

Canonical Correlation Analysis (CCA)

Many works reported in the literature utilised the concept and potential of CCA for denoising artifacts from EEG signals. It is a statistical technique used to connect two sets of datasets to identify maximally correlated. CCA also used second-order statistics, which has reduced computational cost compared to ICA [57]. CCA can be mathematically expressed from equations (4) and (5) as follows:

$$u = w_x^T X(t) \quad (4)$$

$$v = w_y^T Y(t) \quad (5)$$

Where

u and v are canonical variates while w_x and w_y are the weight vectors.

$X(t)$ is the EEG signals in the time domain, and $Y(t)$ is the source signal that is delayed version as described in equation (6):

$$Y(t) = X(t - 1) \quad (6)$$

The weight vectors w_x and w_y can be found when the mean of each row from X and Y signals was removed.

CCA has outperformed ICA in some previously reported studies, especially in removing muscle artifacts because ICA does not eliminate muscle artifacts very well due to missing stereotyped tomography in this type of artifact [45]. Moreover, in CCA, no Gaussian distribution and orthogonality assumption is required in ICA and PCA [46].

Morphological Component Analysis (MCA)

MCA is used to decompose the EEG signal by using the theory of independent redundant transform and sparsity to decompose an EEG signal into different components with different morphological aspects. Those EEG signal components can be represented as a sparse linear contribution of coefficients with various waveforms or atoms in an overcomplete dictionary describing various EEG signal sources [47].

An explicit dictionary representing the specific morphologies of the EEG signal is called the overcomplete dictionary Φ and is represented by a set of mathematical functions of waveforms or atoms. Signal S can be represented as in equation (7):

$$S = \Phi \alpha = \sum_{i=1}^m \Phi^{(i)} \alpha^{(i)} \quad (7)$$

$$\text{Where } \Phi = [\Phi^{(1)}, \Phi^{(2)}, \dots, \Phi^{(m)}],$$

$$\alpha = [\alpha^{(1)}, \alpha^{(2)} \dots \alpha^{(m)}],$$

$\alpha^{(i)}$ is the coefficient vector corresponding to the dictionary $\Phi^{(i)}$. $S^{(i)} = \Phi^{(i)} \alpha^{(i)}$ It represents every component of a signal that has different morphological structures. So, the dictionary $\Phi^{(i)}$ is very useful in separating different signal components as a morphological structure that is sparse in a particular dictionary. $\Phi^{(i)}$ will generally not be sparse in other dictionaries.

MCA performs better than other wavelet transformants, such as stationary wavelet transform [48]. However, this method's major drawback is that each artifact database with its morphological components needs to be available and render its performance to depend on the artifact template available [49].

Wavelet Analysis

Wavelet transform (WT) is a popular approach in biomedical signal processing due to its oscillatory nature [63], finite in length as well suitable in dealing with nonstationary and transient biomedical signals [50]. For example, in EEG signals denoising, WT decomposes the signals into various components using scaling and shifting functions over the whole signals to obtain a signal component in time and frequency domains simultaneously. After calculating the wavelet components, the artefacts' components can be discarded, while the remaining components, mainly the high-frequency part, are used to reconstruct the original clean signal [51]. Generally, wavelet functions can be defined in equation (8) as:

$$\Psi_{s,\tau} = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-\tau}{s}\right) \quad (8)$$

Where s is called scale parameter and τ , the shift parameter

From equation (9), Wavelet transform is given as:

$$\gamma(s, \tau) = \int f(t) \Psi_{s,\tau}^*(t) dt \quad (9)$$

While equation (10) defined Inverse wavelet transforms as:

$$f(t) = \iint \gamma(s, \tau) \Psi_{s,\tau}(t) d\tau ds \quad (10)$$

In discrete wavelet transform (DWT), low pass filter $g[n]$, and high pass filter $h[n]$, which corresponds to scaling and shifting functions, respectively, were designed [52] as Quadrature mirror filters successively. These filters produced approximation coefficients and detail coefficients, as shown in Fig. 7. The decomposition level should be chosen so that the filtering and decimation process continued up to that level [53].

Let an EEG signal $x(n)$ be decomposed into multiple frequency bands of different scale (j); the length of the signal N satisfies equation (11):

$$N = 2^j \quad (11)$$

The decimation process is implemented at each level by down sampling the frequency in half to obtain good frequency resolution. The detail coefficients, which contain the very noisy components, are set to zero as most of the signal information lies in the approximate coefficients (low-frequency component). This process is also known as thresholding. However, [54,55] addressed the limitation associated with deciding thresholding values for detail coefficients. Recent works that used wavelet decomposition to remove EEG artifacts include [56-58], where most of the works reported in the literature combined this approach with another technique. The details of the reported works of wavelet transform combined with other methods were discussed in section 4.0.

Empirical Mode Decomposition (EMD)

EMD is an adaptive time-space method of breaking down a time-domain signal into modes (intrinsic mode functions, IMFs) with the benefits of flexibility, and the basis functions are adaptively derived directly from input data. Apart from analysing the signal components as IMFs, they can form a complete and almost orthogonal basis of a given original signal. Compared with other decomposition methods like Fourier transform and wavelet transform, EMD decomposes the signal into IMFs obtained by analysed sequence and not analytically set. Therefore, it performs better than some existing methods, such as BSS and PCA. Furthermore, EMD is good in eliminating high-frequency components since the first IMF, as given in equation (12), contains the highest frequency components. Sifting is the process of removing an IMFs, and the process is as follows [59]:

Step 1: Locate all the local minima and maxima of the given signal

Step 2: Using cubic spline interpolation, estimate the upper envelope by interpolating between local maxima

Step 3: Repeat step 2 to obtain lower minima using a lower envelope

Step 4: Find the difference between the mean m_1 of the two envelopes and the original signal

Repeat steps 1-4 until the stoppage criterion is achieved.

$$h_1 = S(t) - m_1 \quad (12)$$

Where h_1 is the first component which should ideally satisfy an IMF definition.

Based on the stoppage criterion, the sifting process would continue until the final residue $r(t)$ is constant, which is a function with only one minima or one maxima and any other IMFs to be obtained. The Decomposed signal is finally represented in equation (13) [59]:

$$S(t) = \sum_{i=1}^p h_i(t) + r(t) \quad (13)$$

Where p is the total number of IMFs

Several works have been reported in the literature using EMD to successfully eliminates artifacts from the EEG signal [60]. Some modifications to EMD to enhance its efficiency in eliminating artifacts and using EMD combined with other techniques have also been developed [61-63].

Filtering Technique

Several filtering approaches have been developed by researchers over the years, from the simple classical approach [64] to an adaptive approach [65] and linear filters [66]. Kalman's filter, Weiner filter, and Bayes filters are some of the common filtering approaches. However, adaptive filtering is the most popular filtering approach. Adaptive filtering, unlike the simple filtering technique that used a fixed frequency range, is adjusting its weights after estimating the artifacts signal using a reference signal. The clean EEG signal is obtained after subtracting the estimated artifactual components. It is easy to use; no calibration requirements, and can be implemented online. However, using reference signals in this technique which requires additional sensors, increases its cost and complexity.

The structure of adaptive filtering is shown in Fig. 8. $d(n)$ is the desired signal, $x(n)$ is the reference signal, $y(n)$ is the adaptive filter estimated output, and $e(n)$ is the residual error which is given in equation (14):

$$e(n) = d(n) - y(n) \quad (14)$$

Adaptive filter used optimisation algorithms to help in adjusting its weights to obtain optimum filter coefficients. Recursive least squares (RLS) is one of the best and standard optimisation algorithms employed in adaptive filtering [67]. The least mean squares (LMS) algorithm is another optimisation algorithm used in the adaptive filtering technique [68-70].

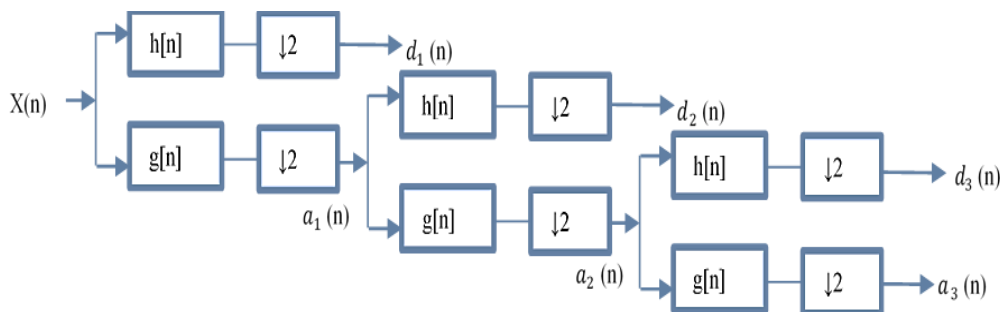


Figure 7: Discrete wavelet decomposition

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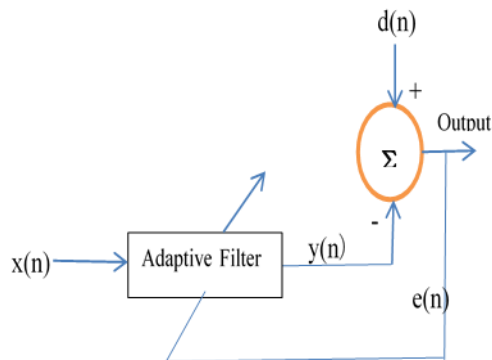


Fig. 8. Adaptive filtering method

Hybrid Techniques

Recently, research has focused on combining two or more methods mentioned above to overcome the limitations of those methods. It utilizes their comparative advantages to enhance the efficiency and accuracy of removing artifacts from EEG signals, as each method has its advantages and disadvantages.

Adaptive Filtering and Blind Source Separation

This hybrid method combines adaptive filtering and blind source separation methods to remove artifacts from EEG signals. Using (BSS_ICA), the ICA technique decomposes the EEG signal into independent components (ICs). Because the artifactual ICs still contains some weak brain signal, removing these ICs causes some distortions in EEG signal. Therefore, adaptive filtering is employed to process the artifactual ICs further to maintain weak neuronal information in ICs [33]. Some research works were carried out as a hybrid method using adaptive filters and BSS techniques, such as in [71,72]. Another method in which cascaded filters are combined with ICA was proposed in [73].

Empirical Mode Decomposition and Blind Source Separation

This method combines EMD and BSS to eliminate artifacts in EEG signals. IMFs are determined using the EMD method from the original EEG signals. After that, the BSS

technique is applied to the IMFs to recognise and eliminate artifactual components [74,75].

Wavelet Transform and Blind Source Separation

Some researchers combined wavelet transform and BSS methods such as ICA and PCA to eliminate noise and artifacts in EEG signals. Two approaches are employed in this hybrid method. One is to start applying the BSS method and then followed by wavelet transform or vice versa. For the first approach, the artifactual components are obtained by decomposing EEG signals. Artifactual components are further decomposed using wavelet transform; thresholding is then applied to the decomposed signal to remove artifacts and finally reconstruct the clean EEG signal [76,77]. Stationary wavelet transforms (SWT) using kurtosis-based strategy was proposed as a low complexity method to remove and correct electrical shift and linear trend artifacts [78]

Support Vector Machine and Blind Source Separation

To further extend and explore the BSS approach's capability, the BSS is combined with SVM technique to improve the separation and elimination of artifacts in EEG signals. This hybrid technique decomposed the EEG signal using the BSS method into various components; features like statistical, temporal, and spatial features are extracted. SVM classifier would then classify the artifact components with the features extracted as input to the classifier. Lastly, the artifact-free signal is reconstructed from the remaining components [79,80].

Adaptive Filtering and Empirical Mode Decomposition

Adaptive filtering combined with empirical mode decomposition is another hybrid technique used to eliminate artifacts from EEG signals by using EMD to decompose the signal into IMFs and using power spectrum components to obtain the frequency of every component, the range of frequency is obtained from a reference artifactual component with least portion of energy

[81]. Thus, the signal can be constructed from the components with a frequency higher than the given range. Then, an adaptive filtering method is applied to eliminate the artifacts and construct the clean EEG signal [82].

Adaptive Filtering and Wavelet Transform

This technique combine wavelet transform and adaptive filtering by decomposing the EEG signal using wavelet transform and applying the threshold method to its coefficients. The Inverse wavelet transform, a recovery transform, is used to reconstruct the reference signal. Finally, adaptive filtering is applied to original EEG signals with reconstructed reference signals as input to obtain an artifact-free EEG signal [83,85].

Other Techniques

Apart from the techniques highlighted above, such as BSS, EMD, wavelet analysis, and filtering techniques, there are few other techniques with promising results in artifact elimination from EEG signals. Multivariate EMD and CCA have been used to denoise muscle artifacts [86]. A method to discard EEG artifacts such as heartbeat and eye blinks during the prediction of traumatic brain injury patients involved dividing the EEG into epochs and further dividing into segments. Spectral power is used to analyse different windows, thereafter discarding the windows that exceed a certain threshold [87]. A hybrid technique that combines regression and BSS technique in denoising ocular artifacts has been presented [88].

Ghaderi et al. [89] reported a review of eye blinks artifact rejection methods and compared the performance of those methods. Machine learning techniques have been proposed in [90]. They use a supervised machine learning algorithm by labelling the data into an expert's standard EEG signal or artifact. The training data is used to train the classifier and classify the input EEG data. Due to the increase in the amount of data available in the health care sector and the need for handcrafted features in traditional denoising techniques, deep learning algorithms have now been applied in EEG denoising.

The deep learning technique can handle large amounts of data, and the raw EEG data can be supplied to the network directly without extracting features separately [91-93]. A convolutional neural network is one of the most popular and common deep learning architectures proposed to eliminate EEG signals' artifacts, as reported in [94-96]. Other deep learning architectures have been experimented with by researchers, such as sparse autoencoders and recurrent neural networks [97-100]. Many research efforts have been devoted to deep learning algorithms to exploit these networks' ability to eliminate EEG signals' artefacts and noise [101].

This review also considers artifact elimination in BCI applications. Researchers believed that the only source of the control signal is from neurological phenomena. Hence, artifacts from sources other than the brain can significantly interfere with the desired control signal and easily mistakenly be used as control signals or change neurological phenomena' characteristics. This problem, if not carefully addressed, can degrade the performance of the BCI system. Therefore, automatic methods need to be developed for real-time and a robust BCI system to deal with this artefact problem in BCI.

Among the methods developed to tackle the artifact-related problem in BCI is Chang et al. [102], in which they used a digital filter that has automatic thresholding to identify and eliminate eye blinking artifacts in real-time. Yong et al. [103] developed a real-time method to automatically eliminate ocular artifacts in the BCI system by employing a stationary wavelet transform combined with an adaptive thresholding technique. Recently, a filter that estimates minimum noise for automatic artifact removal in EEG signals was developed by Foodehet al. [104]. Another recent study by Dhindsa et al. [105] utilized a machine learning approach to develop an automated real-time scheme for removing artifacts by extracting the features when the data is divided into several frequency bands. This method can be used in a few channels of EEG signals. Other recent methods of artifact removal for BCI applications are reported in [106-108].

Performance Evaluation

In order to measure the effectiveness of an algorithm in removing artifacts from EEG signals, performance metric evaluation must be carried out. Simulated EEG data has been reported to overcome the problem of hidden neuronal activity unknown in the recorded EEG signal, thus making it a complex task to evaluate the algorithm's performance. However, experimental data should also be used to evaluate the algorithm's performance due to artifact contamination differences. Mannan et al. [86] listed three stages in which each algorithm should follow to verify its performance as given:

1. Simulated EEG data should be used to verify the algorithm's performance
2. Evaluate the performance using experimentally recorded EEG data
3. Available EEG signals from authentic EEG databases could also be employed to verify the algorithm's performance.

Evaluation Metrics for Simulated EEG Data

Any combination of the performance metric equations (15)-(23) has been used to measure EEG artifact removal algorithm performance. In this procedure, the real EEG data is known and can be easily employed to evaluate the algorithm's performance.

Mean Square Error (MSE.)

$$MSE = \frac{1}{N} \sum_{i=1}^N (EEG_{out}(i) - EEG_{in}(i))^2 \quad (15)$$

Where $EEG_{in}(i)$ is the original EEG, while $EEG_{out}(i)$ is the recovered EEG.

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (EEG_{out}(i) - EEG_{in}(i))^2} \quad (16)$$

It is used to evaluate the distortions at the local regions of the EEG.

Normalized Mean Square Error (NMSE)

$$NMSE = \frac{\sum_{i=1}^N (EEG_{out}(i) - EEG_{in}(i))^2}{N \sum_{i=1}^N EEG_{in}(i)^2} \quad (17)$$

NMSE is used to quantify the extent of deviation from the EEG_{in} . The smaller the NMSE, the better the algorithm.

Relative Error (RE)

$$RE = \frac{|EEG_{out} - EEG_{in}|}{|EEG_{in}|} \quad (18)$$

Signal to Artifact Ratio (SAR.)

$$SAR_Q = \frac{\frac{1}{N} \sum_{n=1}^N |EEG_{in}|^2}{\frac{1}{N} \sum_{n=1}^N |EEG_{con} - EEG_{in}|^2} \quad (19)$$

Where SAR_Q is the signal to artifact ratio before denoising while SAR_P is the signal to artifact ratio after denoising and EEG_{con} is the contaminated/noisy signal.

$$SAR_P = \frac{\frac{1}{N} \sum_{n=1}^N |EEG_{in}|^2}{\frac{1}{N} \sum_{n=1}^N |EEG_{out} - EEG_{in}|^2} \quad (20)$$

$$\gamma = 10 \log \left(\frac{SAR_P}{SAR_Q} \right) \quad (21)$$

$\gamma > 0$ means improved Signal to Artifact Ratio.

1. Mutual Information (MI)

$$MI = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \log \frac{f(x, y)}{f(x)f(y)} dx dy \quad (22)$$

The joint probability density functions (pdf) are denoted by $f(x, y)$ while $f(x)$ and $f(y)$ are the marginal pdfs. A high MI value means the EEG_{in} and the EEG_{out} are largely correlated.

2. Mean Absolute Error (MAE.)

It is a useful metric for estimating the distortion in the frequency bands of the original input and recovered EEG signal.

$$MAE = |P'_{in} EEG - P'_{out} EEG| \quad (23)$$

P' is the power spectral density of the signals

Evaluation Metrics for Real EEG Data

Providing a general metric for evaluating denoising algorithm performance for real EEG data is an area still under research. This is due to the absence of the original noise-free EEG signal for comparative studies. However, there has been a significant contribution to the validation of ocular artifact correction by Pham et al. [109]. His work improves the Croft et al. [110] scheme by

eliminating its limitations. This scheme employs the correlation between the recovered EEG signal and the EOG reference channel for validation.

The drawbacks are the inadvertent inclusion of irrelevant data through the use of a whole epoch for validation of standard deviation and the EOG signal dependence for the validation. However, the validation metric proposed by McMenamin et al. [111] on EMG noise is very difficult to implement even though it sort to evaluate the level of artifact suppression and neuronal signal preservation. Hence, expert's visual evaluation of EEG signals has been used over the years to validate the efficacy of noise suppression algorithms in real EEG signals. This practice is, however subjective.

DISCUSSION OF FINDINGS

It has been established that EEG is a very useful biomedical signal but plagued with noise from different sources. The removal or suppression of these artifacts is essential for accurate EEG signals in disease diagnoses and BCI applications. The challenge is often with the physiological artifacts as the none-physiological ones can be easily corrected with the carefully controlled procedure. EMG artefacts suppression appeared to be the most studied from the literature survey, with 34% as shown in Fig 2. This result is because EMG is still the most difficult artefact to remove from EEG as it does not have a reference signal and often unpredictable pattern. EOG and ECG artefacts, on the other hand, have measurable reference signals and thus are easier to remove, hence their 28% and 15% study frequency respectively.

From Fig. 1, regression appeared to be the most used, followed by ICA at 24% and 22% respectively. Even though the regression approach has drawbacks such as the need for a reference channel and bidirectional method, it tends to have a high percentage as it is still the gold standard for evaluating the performance of new approaches and is highly used in hybrid methods. ICA, a variant of BSS, is much preferred by researchers as it corrects for the limitations in the regression method. However, it tends to lose useful neuronal information due to its non-

consideration for spatio-temporal relations with sources. CCA, another variant of BSS, with a low computational cost and suitable to be implemented in real-time, has thus catered for this drawback.

Some factors influence the choice of a particular technique; for example, real-time signal processing is required in some EEG practical applications. Therefore, an automatic approach such as SVM is required and low in computation such as CCA, so that the method can automatically identify and remove the artifact with little manual intervention. In addition, the choice of denoising algorithm is channel dependent. EMD and wavelet methods can be used on a single channel since they can decompose the single channel into several components. This channel decomposition makes them suitable, especially for portable health care facilities and home care systems usually designed with few channels. Note that channel reduction often increases computational cost, and this is not ideal for BCI applications. However, BSS methods such as CCA and ICA required a large number of channels to provide more accurate results. Furthermore, due to the presence of a different types of artifacts, an automatic approach is not usually general as it may not be able to remove all artifacts. The presence of a reference channel greatly reduces the complexity of a denoising algorithm but limits the number of artifacts it can suppress.

In terms of BCI application, filtering and regression methods have some advantages of real-time, online, fast, and require no pre-processing, making them suitable for practical BCI implementation. Besides, BSS does not require any extra reference signal, thus can be used to eliminate any type of EEG artifacts. Wavelet transform, is very suitable for biomedical signal analysis because it deals with their nature of non-stationarity. However, in EEG analysis, the wavelet method fails to eliminate artifacts whenever the spectral components of brain activities overlap with artifacts. Therefore, recently most researchers focused their attention on combining different techniques to explore and utilise their efficacy. Mannan et al. [86] combined ICA and regression approaches to implement an

automatic denoising scheme with improved performance. Yang et al. [45] proposed an optimised algorithm using CCA and EEMD, while Chen et al. [73] recently developed a scheme for few channel EEG analyses using CCA and multivariate EMD for muscle artifact removal. Many other studies have shown improved performance with hybrid schemes [75-77].

Furthermore, automated and real-time/online EEG signal processing using machine learning algorithms has seen a recent surge in the research community, which indicates the potentials of this state-of-the-art technology in EEG artifact removal. One of the recent works in this approach is Weitong et al. [102], who uses one-dimensional ResCNN deep learning model for optimal artifact removal from EEG signal. A hybrid system of deep auto-encoder and wavelet transform using sparse data was implemented by Nguyen et al. [100] for the removal of EOG artefacts. Due to the comparative advantage of the hybrid system, the algorithm performed excellently in the automatic suppression of EOG artifacts from online real-time signals. Several other recent applications of artificial intelligence and deep learning models in EEG signal denoising [93-95]. There has been increasing application of dry electrodes in EEG signal acquisition. Hence, research should be geared towards the studying noise removal using these dry electrodes compared to the wet ones.

Table 3 gives the comparative analysis of the main methods in tabular form. The table summarized each method's performance in terms of theoretical, computational complexity, online or offline, denoising quality, channel setting, among others.

CONCLUSION

Artifacts from physiological and non-physiological sources always contaminate the EEG signal, affect its quality and alter the results. Therefore, pre-processing to eliminate artifacts/noises is crucial in systems that utilised EEG as control or diagnostic signal in research and clinical applications. Many researchers have investigated and reported different EEG noise elimination methods in the last decade. However, this remains an active research topic as proposed algorithms tend to have one limitation over the years and new schemes are being developed using new technologies.

This paper highlights the progress in removal of EEG artefacts and the advantages and challenges of various methods. Conclusively, our review shows that every method has some advantages and disadvantages, and there is no single method that can be used optimally to remove all types of artifacts in EEG signal processing. Besides, most techniques consider specific applications while ignoring others. Therefore, they may be suitable in one application and not in others. Optimised solution and application-specific approaches need to be investigated and developed to provide an effective, suitable, and efficient artifact rejection system in the future. Finally, the recent trends of combining machine learning approaches with conventional techniques and deep learning applications in EEG denoising should be further explored as it holds the potential of optimal removal of several artifacts at once.

Table 3: Comparative Analysis Of Different Denoising Methods

Method	Reference electrode	Prior knowledge	Computational complexity (Theoretical)	Online	Automatic	Channel setting	Denoising quality
Adaptive filters	Yes	No	Low	Yes	Yes	Single	High
Weiner filters	No	Yes	High	No	Yes/No	Single	High
ICA.	No	No	High	No	Yes/No	Multi	High
EMD.	No	No	Low	Yes/No	Yes/No	Single/Multi	Intermediate

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Method	Reference electrode	Prior knowledge	Computational complexity (Theoretical)	Online	Automatic	Channel setting	Denoising quality
Linear filters	No	No	Low	Yes	Yes	Single	Low
PCA.	No	No	Intermediate	No	Yes/No	Single/Multi	Intermediate
Wavelet transform	No	No	Low	Yes	Yes	Single/Multi	High
VMD.	No	No	High	No	Yes/No	Single	High
Linear regression	Yes	Yes	Low	Yes	No	Single/Multi	Intermediate
EEMD	No	No	Intermediate	Yes/No	Yes/No	Single/Multi	High
EMD+BSS	No	No	High	No	No	Single/Multi	Very High
SVM+BSS	No	No	High	Yes	Yes	Multi	High

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