Review Article

International Journal of Advanced Technology and Engineering Exploration, Vol 9(88)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2021.874883

EEG artifacts detection and removal techniques for brain computer interface applications: a systematic review

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Received: 27-September-2021; Revised: 16-March-2022; Accepted: 18-March-2022

Abstract

Electroencephalogram (EEG) being the measure to record the electrical activity of the brain acts as a key factor to many brain computer interface (BCI) applications. These recorded EEG signals often get interfered with artifacts of different types such as eye blink, muscle movements, cardiac etc. Such artifacts are to be detected and removed for efficient analysis of EEG signals in pre-processing stage. Hence, this systematic review aims to provide an overview of all the available methods to remove the physiological artifacts. In addition, comparison of all the methods and their performance evaluation metrics are discussed. Relevant 159 papers are considered from the databases such as Scopus, PubMed, Crossref, Web of Science and Google Scholar. Several analyses were made based on the collected information and current challenges for BCI applications in handling artifacts are provided. This paper also provides the details of available open-source tools for pre-processing EEG data and publicly available artifacts databases. Findings show that: a) independent component analysis (ICA) is the most popular single artifact removal method b) ICA-wavelet is the most popular hybrid artifact removal method c) maximum publications are for removal of ocular artifacts and less on muscle artifact removal d) deep learning methods are to be experimented more to improve the performance. Even though there are many methods to remove the artifacts, there is no specific method to remove all the artifacts completely. This review also shows that there are still many open issues and research opportunities to handle EEG artifacts.

Keywords

Artifacts removal, EEG, BCI, ICA.

1.Introduction

Electroencephalogram (EEG) signals can be acquired using different electrodes such as dry electrodes, sticky electrodes, geltrodes etc. The placement of electrodes classifies the brain computer interface (BCI) into invasive, non-invasive and semi-invasive systems. Non-invasive is the most popular method used in medical diagnosis, research experiments and many other BCI systems as electrodes are placed on the scalp. Electrodes placed on scalp usually induce lots of artifacts to the signal by which the signal gets contaminated. These artifacts are to be removed to develop an efficient BCI system [1]. There are many methods available to detect and remove the artifacts. These methods should remove the artifacts by retaining the original neural activity of EEG signal [1].

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Since EEG signal is non-stationary and non-linear, it is difficult to identify the artifact without loss of neural information.

The artifacts may affect the signal in spectral, temporal and in few cases it affects spatial domain as well which makes it difficult to process. In this case, simple filtering is not sufficient to completely remove the artifacts during pre-processing. Hence, many hybrid methods were developed but still there is no single method to detect and remove all types of artifacts [2].

In this context, this paper provides a systematic literature review on types of artifacts, existing methods and comparative analysis on available methods. Further, performance evaluation metrics and available open-source tools for artifact removal are also discussed. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) acts as a guideline for this paper. The objective of this paper is to answer the following research questions (RQs).

- RQ1: What are the available artifacts handling methods? What are the characteristics of each method?
- RQ2: How performance evaluation metrics are used to validate the method and its challenges?
- RQ3: What are the available open-source tools in MATLAB and python?
- RQ4: What are the current challenges in handling artifacts for BCI applications?
- RQ5: What are the recommendations for selection of suitable algorithm?

These research questions aim at providing the detailed study on all the aspects of pre-processing and also helps the researcher to choose the suitable method based on the recommendations by considering the current challenges. Each research questions are addressed in section 3.5 to section 7**.**
The key contributions are summarized as follows.

- A detailed and systematic review for EEG artifact handling in the field of BCI applications.
- An extensive description of literature from the past 22 years (2000-2022) as well as comparison of all the methods and its progress over the years.
- A highlight on the challenges and recommendations for further research based on the findings of this review.

Perusal of literature showed, this paper is the first systematic review on EEG artifact handling methods which provides a roadmap for detailed study on all the methods, its comparison, performance validation and its challenges, open-source tools and databases, challenges and recommendations. Most of the reviews [1, 2 and 3] focused on artifact handling methods by providing comparison on existing methods and less description on challenges and recommendations. Another review [4] solely contributed on the challenges and recommendations with open-source tools. Hence, this paper attempts to include all the aspects including the use of new machine learning and deep learning models in handling the artifacts by addressing the challenges in those methods.

This paper is organized as follows to answer all the research questions (RQ1 to RQ5): Section 2 describes the background of EEG characteristics and artifacts. Section 3 describes the research methodology employed and all the artifact handling methods. Results and discussions are presented in section 4. Section 5 presents performance evaluation metrics. Most popular open-source tools and publicly available artifact databases are presented in section 6. Section 7 presents the current challenges and recommendation. Finally, section 8 concludes the paper.

2.Background

In this section, overview of EEG characteristics and types of artifacts are discussed.

2.1EEG

EEG captures the electrical activity of brain using electrodes. Its frequency range varies from 0.1 to 100Hz [1]. This is classified as bands depending on the frequency and mental state of a person as delta, theta, alpha, beta and gamma bands. These bands with their frequency and associated mental state are shown in *Table 1.*

Table 1 EEG bands with their frequency and associated mental state

Band	Frequency (Hz)	Status
Delta	<4	Deep Sleep
Theta	4-8	Drowsy
Alpha	8-13	Relaxed state
Beta	13-35	Active Thinking
Gamma	>35	Peak Performance

2.2Artifacts

The artifacts can be due to physiological/internal or non-physiological/external sources. Ocular, muscle, cardiac, perspiration and respiration are categorized as internal artifacts due to physiological activities. Instrumental, interference and movement artifacts due to electrodes, cables, sound, electromagnetic etc., are categorized as external or non-physiological artifacts [5]. *Table 2* shows different types of artifacts and their source.

Artifact removal seems to be challenging and the main reason for not having a suitable algorithm to remove all the artifacts is due to electrical characteristics. The frequency of ocular artifacts ranges from 0.5-3Hz where it affects delta and theta band. For muscle artifact, frequency is less than or equal to 35Hz which affects delta and gamma band. Cardiac artifact has greater than 1Hz frequency and it overlaps with EEG signal. This overlap makes it difficult to observe the cardiac artifact with naked eye. Another internal artifact called perspiration has very low frequency and affects delta and theta band. The external artifacts such as mobile phone interference and electrode artifact has high and very low frequencies respectively but they are different from all the bands. Transmission noise has 50-60Hz frequency range which affects gamma band. This overlap and effect on EEG bands makes it hard to eliminate the artifact. These characteristics along with the amplitude are summarized in *Table 3* and it clearly describes that differentiation of artifacts and EEG band becomes very difficult as they have nearly same frequency range [6].

Table 2 Types of artifacts and their sources

Type	Source
Physiological/internal artifacts	
1. Ocular Artifacts	Eye Blink, Eye movement, Rapid eye movement (REM) sleep, Eye flatter
2.Muscle Artifacts	Clenching, muscle tension, hiccupping, swallowing, chewing, talking, sucking, sniffing,
3.Cardiac Artifacts	Pulse, Cardiac activity
4. Perspiration	Skin potentials, sweating
5. Respiration	Inhale and exhale
Non-Physiological/external artifacts	
1. Instrumental	Electrode pop, cable Movement, Incorrect reference placement
2. Interference	AC Electrical, Sound, electromagnetic, Optical
3. Movement	Body and Head movements

Table 3 Electrical characteristics of artifacts

Artifact	Frequency	Effect on frequency domain	Amplitude
Ocular	0.5-3 Hz	Delta and Theta band	100mV
Muscle	<=35Hz	Beta and Gamma band	Low
Perspiration	Low	Delta and Theta band	Low
Cardiac	>1Hz	Overlaps EEG and difficult to visualize with naked eye	1-10mV
Transmission noise	50-60Hz	Gamma Band	Low
Mobile phone interference	High	Different from all the bands	High
Electrode	Very Low	Different from all the bands	High

3.Methods and materials

This systematic review was performed using the PRISMA method as it gives the apparent guidelines for systematic review and meta-analysis. It includes 3 main stages i.e., literature survey, choosing the relevant papers, and extracting the information and summarizing.

3.1 Eligibility for selection of papers

The eligibility criteria focused on selecting the papers which tries to address the research questions presented in first section. The work focused on methods used for handling physiological artifacts for real or simulated EEG in BCI applications. The selection was based on scalp EEG as it is most popular in real-time BCI applications compared to invasive methods. In addition, epileptic, sleep and other disorders are not considered.

3.2 Search source

The most popular search engines such as Scopus, Google scholar, Crossref, Web of science and Pubmed were used. Special dedicated software called "Publish or Perish" is used for collecting the initial information. The main reason behind using this software is that it helps to do initial screening since the entire search results can be downloaded in the required format (CSV, JavaScript object notation (JSON), Bibtex file formats etc.). It includes the indexing from many digital libraries like IEEE, Elsevier, ACM, Springer, PLOS, Wiley, Taylor & Francis etc. The downloaded search result in comma separated value (CSV) file includes many details such as: title, year, author, source, citeURL, articleURL, publisher, abstract etc. This information was very useful to do initial screening of abstracts so that only relevant paper can be included. It helps to recognize the peer-reviewed journals and conferences significant for the study. The link to download "Publish or perish" software is as follows: https://harzing.com/resources/publish-or-perish. This is available for windows, Linux and macOS. The only drawback is that it will give maximum 1000 results at a time. Hence, relevant keywords and year can be provided and iterated to download more results.

3.3 Search keywords

The keywords used are mainly for scalp EEG BCI applications. The Boolean OR operator and Boolean AND operator was used to connect the keywords during search. The resultant string for identification of methods was as follows:
(“BCI” or “Brain Computer Interface” or “EEG” or “Electroencephalogram” or “Mind-controlled” or “Brain machine interface”) AND (“Artifact removal” or “Artifact detection” or “Artifact Identification” or “Artifact Correction” or “Artifact reduction”) AND (“Methods” or Hybrid method” or “Machine learning” or “deep learning”)

3.4Study selection

A total of 2792 articles were identified from the databases and found relevant for the study. A total of 1190 duplicates were removed before starting the initial screening, resulting in 1602 articles. After the review of title and abstract of remaining articles, 1203 articles were excluded based on the eligibility criteria, reducing the total to 399. These full text articles were reviewed again based on the relevance to answer the RQ’s and excluded 240 articles from the study. The articles with same methodology and artifact types, articles with sleep, epileptic or other disorders were excluded. This study concentrated on scalp EEG since it is most relevant for BCI applications. For quality review, finally a total of 159 papers were considered. *Table 4* shows the inclusion and exclusion criteria used in selection of the publications. The timeline distribution of selected articles by year is shown in *Figure 1*. *Figure 2* shows the distribution of selected papers from different publishers. The complete process is shown in PRISMA flow diagram in *Figure 3.*

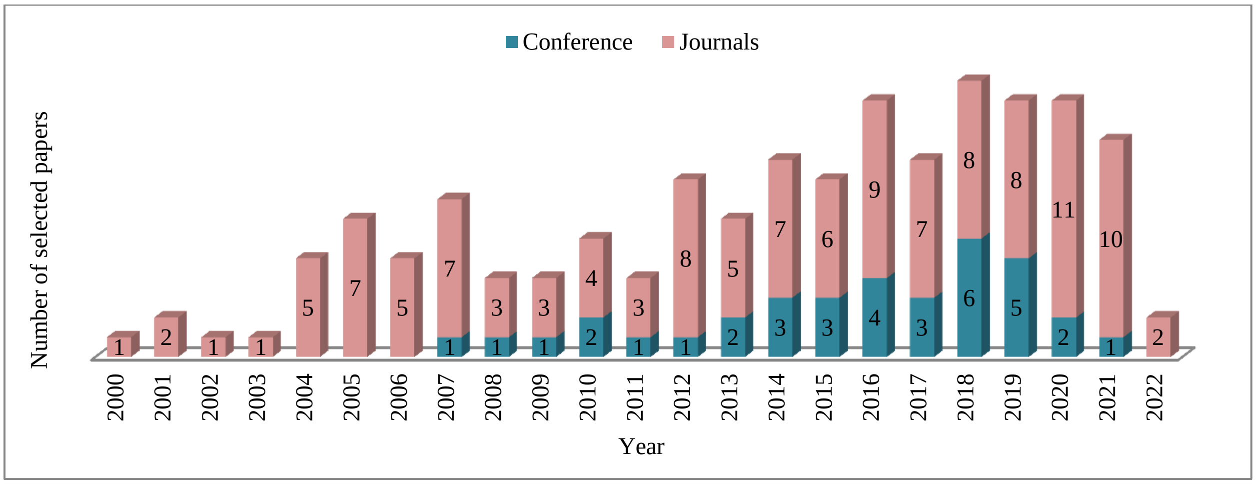

Figure 1 Timeline distribution of selected papers published per year

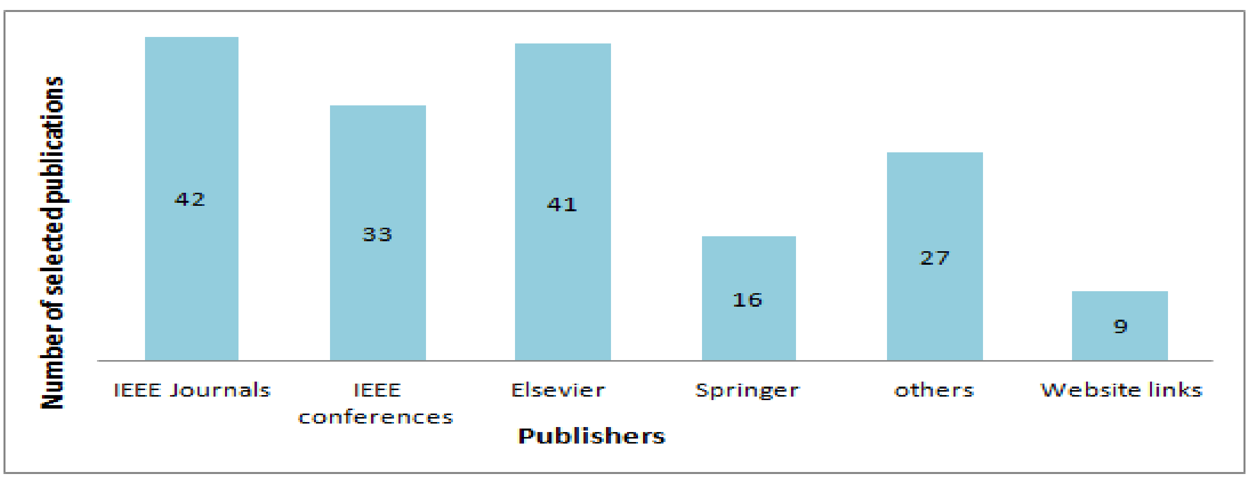

Figure 2 Distribution of selected papers from different publishers

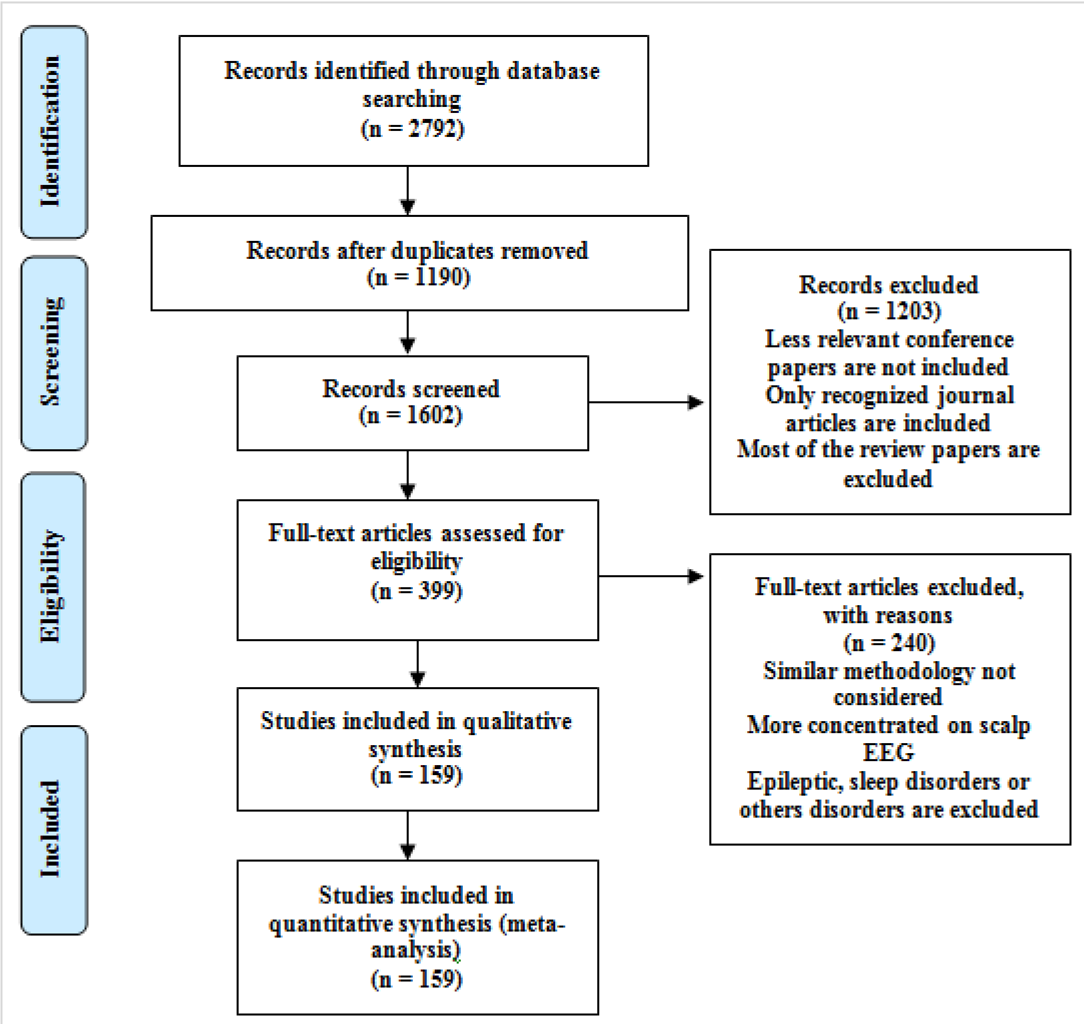

Figure 3 Prisma flow diagram for selection of papers

Table 4 Inclusion and exclusion criteria for paper selection

Inclusion criteria	Exclusion criteria
• Scalp EEG signals are considered. • Included both Real-time EEG and simulated EEG signals. • Papers with Open source tools for artifact removal are also considered. • Only Peer-reviewed journals and conference papers are considered (IEEE, Springer, and Elsevier etc). • Study selection year is between 2000 and 2022. • Most of the selected publications include validation criteria such as mean square error (MSE), signal-to-noise ratio (SNR), artifact to signal ratio (ASR), root mean square error (RMSE) etc.	• Invasive EEG signals are not considered (ECoG etc). • EEG with disorders is not considered (Ex: Epilepsy, Depression, sleep disorders etc). • Many papers with similar techniques and algorithms are excluded. • Most of the review papers are excluded. • Papers with EEG-fMRI are excluded.

3.5 Artifacts handling methods

Artifact avoidance

Some of the artifacts can be avoided as a precautionary measure by following few steps during EEG signal acquisition. It can be informed to individual subjects to stay relaxed without any body movement and avoid eye-blinks as much as possible. For some of the applications with imaginary EEG signals, eyes can be closed which eliminates eye blink artifacts. But this cannot be a practical solution for all the applications. Also care must be taken for placement of reference electrodes to reduce the external artifacts [1−7].

Artifact detection

Artifact detection is the most important step and this should be detected at a beginning stage to efficiently continue the processing for any application. Some of the methods are independent component analysis (ICA), machine learning and artificial neural networks. The selection of artifact method depends on the application [7].

Artifact segment rejection

This method rejects the segment or channel which causes the artifact. The major drawback of this method is that it also eliminates the important neural activity. This leads to inefficient BCI applications [1−7].

Artifact removal methods

Artifact removal eliminates or corrects the artifact without affecting the characteristic of raw signal. It can be done using regression, filtering or decomposition techniques. These are broadly classified as single stage and hybrid methods and they are discussed in 3.5.5 and 3.5.6

Single artifact removal methods

Regression model: It is the simple and linear model to remove the artifact. It considers that EEG is contaminated with electrooculography (EOG) and tries to eliminate the ocular artifact with simple subtraction. This method uses one or more reference channel to identify and remove the artifacts. The linear model with raw EEG, observed EEG and EOG can be represented in Equation 1.

$$oEEG_i = EEG_{raw} - \alpha_i vEOG + \beta_i\, hEOG \qquad (1)$$

where α and β are the transmission coefficients between EOG and EEG, oEEG and EEG_{raw} are observed EEG and raw EEG respectively for ith electrode. v and h denote vertical and horizontal EOG channels. The drawback of this method is that it fails when there is no reference channel [8].

Wavelet transform: Wavelet decomposition can be used to remove the artifacts from EEG signal using detailed and approximation coefficients with thresholding. It is defined in Equation 2.

$$WT\, x_n\, [a, b] = < x_n, \Psi_{a,b} > \qquad (2)$$

where $\Psi_{a,b}$ [m] = $|a|^{-(1/2)}$ Ψ [(m-b) / a] and a, b are scale and translation parameters. This gives the decomposition signal. Discrete wavelet transform is the most widely used method which uses high pass filter giving detailed coefficient and low pass filter giving approximation coefficient. Wavelet coefficients are used to remove the ocular artifacts with adaptive thresholding in [9]. The drawback of this method is that it cannot identify the artifact when artifacts are overlapped with the spectral features [10].

Blind source separation (BSS)

BSS is the most popular method of artifact removal. It separates the source signal with neural activity. Generally, when acquiring the EEG signal many neurons get simulated and there is no clear information about mixing up of different sources to EEG signal. BSS considers mixing matrix for original and observed signals and gets the estimated sources of artifacts. This separation of neural activity with artifacts is difficult or sometimes not possible. Hence, there are many methods under BSS and some of them are discussed below [11].

i) Independent component analysis (ICA)

ICA assumes that sources are mutually independent. But it requires manual intervention to remove the artifact as it is not automatic method. Most commonly it is used to remove ocular artifacts and it uses linear transformation under the assumption that sources are mutually independent and non-Gaussian [12−13].

ii) Canonical correlation analysis (CCA)

It reduces the computational time due to the usage of second-order statistics to fetch the components from uncorrelated feature. The sources are separated from uncorrelated sources but in ICA it is from independent source. Artifacts are identified as the components having least auto-correlation. CCA is effective in removing muscle artifacts and it is efficient and automatic compared to ICA [7].

iii) Principal component analysis (PCA)

PCA is used to construct the mixing matrix based on normalized Eigen-vectors of covariance matrix. Coefficients are sorted based on the first largest value of variance which makes them orthogonal. PCA is independent and uncorrelated compared to ICA [12].

iv) Morphological component analysis (MCA)

MCA decomposes the signal depending on the morphology of EEG signal. It is limited to only few artifacts whose morphology and shape is already stored in the database. It is efficient in removing the ocular and few muscle artifacts [2].

Empirical mode decomposition (EMD)

EMD is used for non-stationary, non-linear signal processing. It decomposes the signal using fractional gaussian noise (fGn). This technique can remove artifacts using data adaptive detrending approach. The basis of decomposition in this method is intrinsic

mode function (IMF) which are finite set of amplitude modulation (AM)-frequency modulation (FM) oscillating components. There are two basic conditions to be an IMF:
(i) the number of extrema must be equal (or at most may differ by one) to the number of zero crossings
(ii) at any point, the mean value of the two envelopes defined by the local maxima and the local minima is zero.

EMD process flow is as follows.

1. Detect the extrema (maxima and minima)
2. Generate lower and upper envelopes using cubic spline interpolation
3. Find local mean using lower and upper envelopes.
4. Subtract local mean from original signal so that IMF have zero local mean.
5. Repeat step 1 to 4 until IMF is obtained which satisfies the two basic conditions.

EMD is suitable to remove EOG artifacts and it can be used to implement filtering in time domain [14].

Adaptive filtering

Adaptive filtering can be used to remove the physiological artifacts using the artifacts as the reference signal. The weights are updated iteratively to subtract the artifact from the raw signal as depicted in *Figure 4*

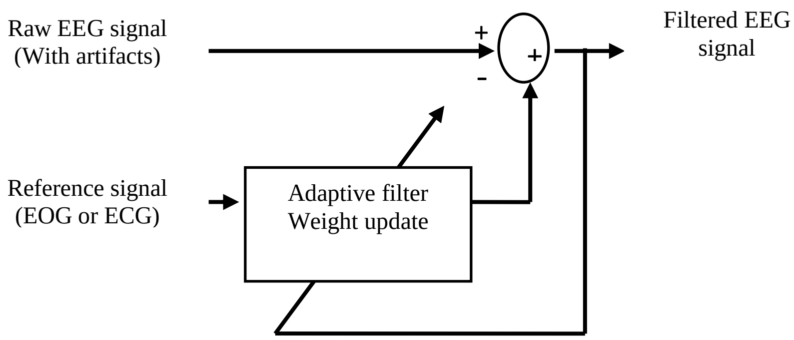

Figure 4 Adaptive filtering method

Adaptive filtering using empirical modes method is proposed in [15] to remove the physiological artifacts. Modes with artifacts are searched in decomposed EEG signal and those modes are removed. Another enhanced adaptive filtering method with neural network is shown in [16] with high Signal-to-noise ratio. It is hybrid method which uses adaptive filtering and neural network to get optimal weights.

Signal space projection (SSP)

In this method, the signals with stable spatial patterns are separated into set of components in multidimensional space but the amplitude varies depending on time. It is used to separate the EEG and electromyography (EMG) signal thus suppressing the EMG artifact in the signal [17]. It works on the assumption that subspace of the neural signal is different or orthogonal compared to artifact signal. Nolte and Hämäläinen [18] have shown signal space projection (SSP) algorithm and its applications in reducing the artifacts for Magnetoencephalography (MEG) recordings. References [19−24] show the usage of SSP method to separate MEG from EEG signal.

Beamforming

Beamforming or spatial filtering is a method used to analyze the brain signals in recent times. This method can be mainly used in source localizations for EEG and MEG analysis. It is designed to allow only neural activities and weaken all internal or external sources. This theory is used to remove the MEG signal from EEG [7]. It has been also used to remove the ocular artifacts as mentioned in [7].

Hybrid methods

Single stage artifact removal methods are not sufficient to remove all the artifacts because of some limitations. Hence, there are many hybrid methods proposed by few researchers to overcome the limitations of single artifact removal methods. Some of the methods are discussed below.

Adaptive filtering and blind source separation (BSS)

Adaptive filtering and BSS is combined to form hybrid method. As discussed in the previous section, BSS has many categories and one such is ICA. Adaptive filtering and BSS with ICA is a hybrid method where signals are decomposed into independent ICs for removing artifacts. But, these ICs may also contain neural activity so it is combined with adaptive filtering. Klados et al. [25] have proposed a hybrid method with BSS, ICA and adaptive filtering to remove the artifacts. The process flow of adaptive filtering and BSS is shown in *Figure 5*. Hybrid ICA is demonstrated by Mannan et al. [8] to remove the ocular artifacts efficiently.

Wavelet and blind source separation (BSS)

It is a combination of wavelet and BSS with ICA or CCA. This method decomposes the signal using ICA or CCA and further signals are decomposed by wavelet transform. Thresholding or denoising is applied to remove the artifacts and signal is reconstructed by using inverse wavelet transform. The process flow is shown in *Figure 6*. Roy et al. [26] have shown hybrid methods of BSS-Wavelet, EMD-BSS with ICA or CCA for removing motion artifacts and best performance was observed with discrete wavelet transform (DWT) combined with BSS.

Empirical mode decomposition (EMD) and blind source separation (BSS)

EMD and BSS combination forms a hybrid approach to remove the artifacts. EMD decomposes the signal into IMFs and followed by BSS to identify the artifactual components and remove those using either ICA or CCA. The process flow of this method is shown in *Figure 7*. Such methods are described in [26−28].

Blind source separation (BSS) and support vector machine (SVM)

BSS combined with SVM is proposed in [29], this hybrid method uses BSS methods to decompose the EEG signal. Further, features are extracted from the decomposed signal and these features are fed as an input to SVM to identify the artifacts. The process flow of BSS, SVM is shown in *Figure 8.*

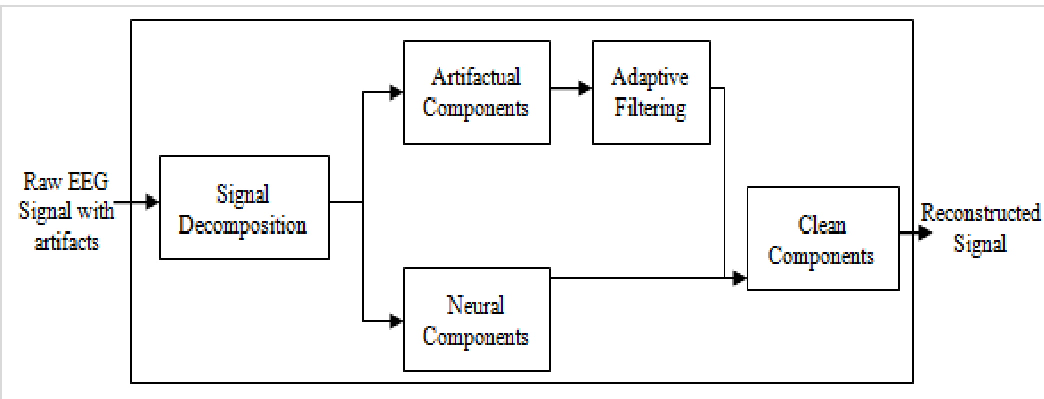

Figure 5: Process flow of adaptive filtering and BSS

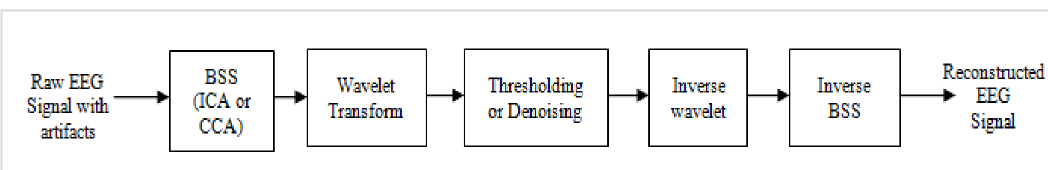

Figure 6 Process flow of wavelet and BSS

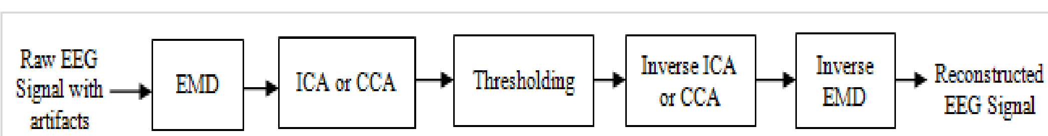

Figure 7 Process flow of EMD and BSS

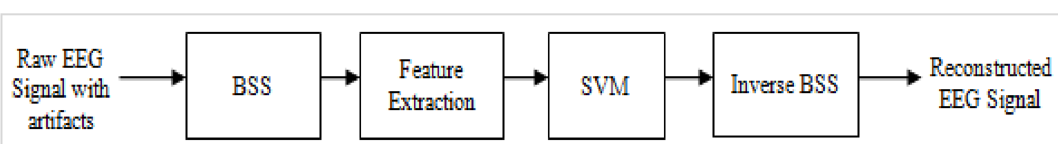

Figure 8 Process flow of BSS and SVM

Other hybrid methods
EMD and adaptive filtering is one of the hybrid method used to remove the electrocardiogram (ECG) artifacts from raw signal as reported in [30]. Adaptive filtering and wavelet combination can remove the ocular artifact as reported in [31]. Wavelet neural network method is proposed in [32] to remove the EOG artifact. This method uses artificial neural network and wavelet transform where EOG reference channel is used in training the neural network. Artificial neural fuzzy inference method and functional link neural network is proposed in [7] to remove EOG and EMG artifacts. Real-time ocular artifact suppression using recurrent neural network is proposed in [33].

4.Results
In this section, comparison of different methods found in the existing literature is discussed. There are various factors to analyze the performance of artifact removal algorithm and these factors sometimes depend on the application. Some of the factors included in our discussion are as follows.

Reference channel
Most of the ocular and ECG artifact removal methods require reference channel for algorithm to be functional. This acts as additional information which helps to identify the EOG or EEG artifacts.

Automated or semi-automated method
To develop an efficient and real-time BCI system, artifact removal should be automatic. Manual method takes much time when it is multi-channel EEG. Hence, some of the methods like BSS, ICA are implemented to detect artifacts automatically.

Real-time/online or offline implementation
It is more related to software processing of EEG data in real-time and these are also automatic systems.

Single or hybrid method
As discussed in section 3, artifact removal can use single or hybrid methods depending on the application and type of artifact to be removed.

Performance metric
It is an important factor to validate the algorithm of artifact removal. It helps to know the efficiency of any method used for real or simulated EEG. Few comparisons are discussed in this section by considering the above factors along with the application. We first compare the single stage artifact removal methods along with the drawbacks and later discuss about hybrid methods. The comparison of single stage methods are as follows.

Regression is used in earlier EEG analysis which need a reference channel for removing artifacts and it was shown by Croft and Barry [34] to remove ocular artifact using EOG as reference. The drawback of regression method is the need of reference channel and it is not applicable for all the artifacts because practically single EMG reference is not available. It can be used for real-time and fully automated systems once it is properly calibrated. In [34] it was not used for real-time application.

He et al. [35], Puthusserypady and Ratnarajah [36], Kher and Gandhi [37] have shown the usage of adaptive filtering methods to remove the ocular artifact and Garces Correa et al. [38] for ocular and cardiac artifact. This method also requires reference channel to remove the artifact similar to regression method. It is not applicable to all the artifacts since EMG robust reference is not available. The difference between regression and adaptive filtering is in need of reference channel and calibration. Regression needs calibration whereas it is not required in adaptive filtering. Both the methods are applicable for real-time and single channel EEG BCI applications. Another method called Kalman filtering was demonstrated by Kierkels et al. [39] and Morbidi et al. [40] which also requires reference channel to remove the artifact.

ICA is the most popular method in BCI applications and it is applicable for all the artifacts. Tong et al. [41] proposed ICA for small animal EEG applications to remove cardiac artifact but it is not fully automatic. James and Gibson [42] have demonstrated ICA for removing all the artifacts but in this work they have used a reference channel to identify the artifact. Joyce et al. [43] used ICA for removing ocular artifact and it is automated with no reference channel. Now there is an improvement in [43] compared to [34, 42] as the system is automated and no reference channel is needed. Tran et al. [44] proposed ICA for removal of ocular and muscle artifact for speech EEG with no reference channel but it was not real-time and automated system. Zhou et al. [45] have shown removal of ocular and power line artifact without the use of reference channel making it automatic but it was not for real-time applications. Flexer et al. [46] and Mognon et al. [47] have demonstrated to remove ocular artifact using ICA. Both were not for real-time applications and Mognon et al. [47] system is for event related potential (ERP) application which is fully automated but [46] is not automated. Along with general EEG applications, ICA can be used for functional magnetic resonance imaging (fMRI) as shown by Nakamura et al. [48] and for neonatal EEG applications indicated by Miljković et al. [49] in removing cardiac artifact. Wang and Jung [50], Turnip [51], Zou et al. [52] and Lakshmi et al. [53] have used ICA to remove all the artifacts and all these are automated systems but only [51] is a real-time application. Few researchers used ICA to remove artifacts due to head movement and muscle activities as depicted by Daly et al. [54] and Mayeli et al. [55]. Most commonly it was used to remove ocular and cardiac artifacts. The drawback of this method is that it is not fully automated since bad IC should be selected manually. This can be made automatic by combining with statistical IC's [47]. Hence, this method is not practically applicable for real-time applications. In addition, it also requires an expertise to select the bad channel.

De et al. [56] have demonstrated CCA for removal of muscle artifact. Chou et al. [57] used CCA for removal of both muscle and ocular artifacts. CCA doesn't require reference channel to identify the artifact. Even though CCA can be used to identify all the artifacts, it is most commonly used for removal of muscle artifact. It is applicable for real-time and automated BCI applications.

Turnip [58] has proposed PCA to detect all the artifacts in EEG signals. This system was real-time and generally PCA's don't need reference channel. Ter et al. [59] have proposed PCA to remove the transcranial magnetic stimulation (TMS) induced artifact for TMS evoked potential EEG applications. BSS methods (ICA, CCA and PCA) are applicable to all the artifacts but applicability to single EEG channel depends on the assumption that number of artifact source must be equal to number of EEG channels. CCA and PCA can be used for real-time applications but not ICA due to manual bad IC selection.

Wavelet transform is another popular method which is applicable for all the artifact detection. Kiamini et al. [60] have proposed wavelet based algorithm for ocular artifact detection and Islam et al. [61] have shown wavelet transform for epileptic EEG application to remove all the artifacts. Even though wavelet transform doesn't require reference channel, it is not fully automated. Thresholding can be used to make wavelet transform a fully automated system. In addition, wavelet Denoising and wavelet packet decomposition are shown in [62, 63] respectively to identify all types of artifacts. Another advantage of wavelet method is that it is applicable for single channel EEG.

EMD is one of the frequency decomposition methods similar to wavelet decomposition. Hence, thresholding should be applied to develop automated applications. Liu et al. [64] have proposed multivariate empirical mode decomposition (MEMD) for removal of motion artifact. Few more details can be found in references [65, 66] and fast multivariate empirical mode decomposition (FMEMD) is proposed in [67] to remove the muscle artifact. EMD may not be applicable to real-time system and it doesn't require reference channel.

Machine learning algorithms were also proposed by few researchers with the improved performance in single stage artifact removal. Shao et al. [68] demonstrated weighted SVM for error correction to eliminate all the artifacts. Artificial Neural network was proposed by Paulraj et al. [69] and Tibdewal and Thakare [70] for removing ocular and muscle artifact. Sleep artifacts were efficiently removed by Saifutdinova et al. [71] using Random forest classifier. *Table 5* provides comparison related to single artifact removal methods.

Table 5 Comparative study on single artifact removal methods from existing literature

Article	**Year**	**Artifact type**	**Method**	**Automated**	**Application**	**Reference channel**	**Online / real-time**
Croft et al. [34]	2000	Ocular	Regression	No	General	EOG	No
Tong et al. [41]	2001	Cardiac	ICA	No	Small animals EEG	No	No
Park et al.[72]	2002	Cardiac	Energy interval histogram	Yes	General single channel EEG Sleep EEG	No	Yes
James and Gibson [42]	2003	All	ICA	Yes	EM brain signals	Yes	No
He et al. [35]	2004	Ocular	Adaptive filter	Semi-	General	Vertical	Yes

Article	Year	Artifact type	Method	Automated	Application	Reference channel	Online / real-time
				automated		EOG and Horizontal EOG	
Joyce et al. [43]	2004	Ocular	ICA	Yes	General	No	No
Puthusserypady and Ratnarajah [36]	2005	Ocular	Adaptive filter	Yes	General	Yes	No
Tran et al. [44]	2004	Ocular and Muscle	ICA	No	Speech EEG	No	No
Flexer et al. [46]	2005	Ocular	ICA	No	General	No	No
Zhou et al.[45]	2005	Ocular and power line	ICA	Yes	General	No	No
De et al. [73]	2005	Muscle	Sub-space method for modeling common dynamics	Yes	General Epileptic Multichannel	No	No
Nakamura et al. [48]	2006	Cardiac	ICA	Yes	General EEG fMRI	No	No
De et al. [56]	2006	Muscle	CCA	Yes	General	No	No
Kierkels et al. [39]	2007	Ocular	Kalman Filter	Yes	General	Yes	No
Correa et al. [38]	2007	Cardiac and ocular	Adaptive Filter	Yes	General	Yes	No
Morbidi et al. [40]	2008	TMS induced artifacts	Kalman Filter	Yes	General	Yes	No
Kiamini et al. [60]	2008	Ocular	Wavelet	Yes	General	Yes	No
Shao et al. [68]	2009	All	Weighted SVM with error correction	Yes	General	No	No
Miljković et al. [49]	2010	Cardiac	ICA	No	Neonatal EEG	No	No
Gao et al.[74]	2010	Ocular	Peak detection of independent component	Yes	General	No	No
Mognon et al. [47]	2011	Ocular	ICA	Yes	ERP	No	No
Wang and Jung [50]	2012	All	ICA	Yes	General	No	No
Chen et al. [75]	2012	Ocular	ICA	Yes	General SSVEP	No	Yes
Daly et al. [54]	2013	Head movement	ICA	Yes	Cerebral palsy	Yes	Yes
Ter et al. [59]	2013	TMS induced artifacts	PCA	Yes	TMS evoked potential	No	Yes
Turnip [51]	2014	All	ICA	Yes	General	No	Yes
Turnip [58]	2014	All	PCA	Yes	General	No	Yes
Paulraj et al.[69]	2014	Muscular and Ocular	Neural network	Yes	General	No	No
Acharjee et al. [76]	2015	Gradient Artifact	Independent Vector Analysis	Yes	fMRI	No	No
Kher et al. [37]	2016	Ocular	Adaptive filter	Yes	General	Noisy EEG and Clean EEG	No
Zou et al. [52]	2016	All	ICA	Yes	ERP	No	No
Mayeli et al.[55]	2016	Ocular, motion, Muscle	ICA	Yes	General fMRI	No	Yes
Chou et al. [57]	2016	Muscle and Ocular	CCA	Yes	General	No	Yes

Article	Year	Artifact type	Method	Automated	Application	Reference channel	Online / real-time
Islam et al. [61]	2016	All	Wavelet transform	Yes	Epileptic General Scalp EEG	No	No
Maddirala and Shaik [77]	2016	Motion	Singular spectrum analysis	Yes	General Single channel EEG	No	No
Lakshmi et al. [53]	2017	All	ICA	Yes	ERP General	No	No
Li et al. [78]	2017	Ocular	Discriminative ocular artifact correction	Yes	General Feature Learning	No	No
Mohammadpour and Rahmani [79]	2017	Ocular	Hidden Markov Model	Yes	General	No	No
Chen et al. [80]	2017	Ocular and Muscle	BSS	Yes	General	No	No
Tibdewal and Thakare [70]	2018	Ocular	Artificial Neural Network	Yes	General	Yes	No
Saifutdinova et al.[71]	2018	Sleep Artifacts	Random Forest classifier	Yes	Multi-channel Sleep EEG	No	Yes
Borowicz [81]	2018	Ocular	Weiner Filter	Yes	General Multi-channel	No	Yes
Islam and Rastegarnia [62]	2019	All	Wavelet Denoising	Yes	Motor Imagery and ERP	No	Yes
Ahmad et al. [82]	2019	Ocular	Stop-band Filter	Yes	General	No	No
Dai et al. [83]	2019	Cardiac	Recursive Least square	Yes	General	No	No
Butkeviči et al.[84]	2019	Movement	Baseline estimation and Denoising with sparsity filter	Yes	General Sports exercise	ECG	Yes
Bajaj et al. [63]	2020	All	Wavelet packet decomposition	Yes	General	No	No
Liu et al. [64]	2020	Motion	MEMD	Yes	General	No	No
Dimigen [85]	2020	Ocular	ICA	Yes	General	No	No
Li et al. [86]	2021	Cross-over artifact	Multiscale entropy analysis	Yes	Rhythmic EEG Sleep	Yes	No
Sawangjai et al. [87]	2022	Ocular	GAN	Yes	General Multi-channel	No	No

Hybrid methods are combination of two or more algorithms developed to improve the performance of artifact identification and correction. Most of the hybrid methods are automated and doesn't require reference channel. The need of reference channel depends on the algorithm used in first stage of pipeline. For example, reference is required if regression or adaptive filtering was used in first stage of pipeline. It's applicability to single channel EEG also depends on the algorithm in first stage. The real-time implementation of this hybrid method is quite complex due to the involvement of two or three methods. ICA with wavelet is the most popular hybrid method as illustrated by Castellanos and Makarov [88], Mammone et al. [89], Zachariah et al. [90], Kaur and Singh [91] for eliminating all types of artifacts. This method was most frequently used to handle ocular artifact as shown by Akhtar and James [92], Ghandcharion and Erfanian [93], Jirayucharoensak and Israsena [94], Mahajan and Morshed [95], Paradeshi et al. [96]. ICA-wavelet can be combined with SVM to remove the ocular artifact as shown by Hsu et al. [97] in single trail EEG systems.

If ICA method is in the last stage of pipeline there is no need of reference channel. Cheng et al. [98] proposed ICA with singular spectral analysis (SSA) for removal of diverse artifacts such as EMG, EOG and ECG simultaneously from single channel EEG.

Devulapalli et al. [99] introduced a hybrid method firefly–Levenberg–Marquardt (FLM) with adaptive filter for optimization of EMG, ECG, EOG artifacts and demonstrated that this method is effective in removal of ocular artifact. Abidi et al. [100] has shown a hybrid method for removal of muscle and ocular artifacts for multi-channel EEG with efficient fast independent component analysis (EFICA) and tunable Q-factor wavelet transform (TQWT) with reduced mean square error. Chen et al. [101] proposed variational mode decomposition (VMD) with CCA for removal of muscle artifact and demonstrated that it is superior method compared to the available methods.

The performance improvement can be seen in hybrid methods if they are combined with machine learning methods. Adaptive filter with neural network was proposed by Jafarifarmand and Badamchizadeh [102] to remove ocular, muscle and cardiac artifact and it is real-time implementation with good performance. Another hybrid method with ICA and auto-regressive eXogenous (ARX) was demonstrated by Wang et al. [103] to remove the ocular artifact. This method was robust since ARX model selects the optimal model and shows the better performance. Dora et al. [104] proposed hybrid method with SSA and neural network regressor (NNR) to remove muscle artifacts from single channel EEG. All these methods when combined with machine learning methods have shown improved performance.

The real-time implementation of any of these algorithms depends on the availability of resources and hardware. One should decide to use the hybrid method based on individual requirements. In hybrid methods, the selection of proper pipeline is very important to get the good performance. For example, hybrid methods may fail to eliminate EMG artifact if regression or adaptive filtering were used in first stages. *Table 6* provides comparison related to hybrid artifact removal methods.

Table 6 Comparative study on hybrid artifact removal methods from existing literature

Article	**Year**	**Artifact type**	**Method**	**Automated**	**Application**	**Reference channel**	**Online/ real-time**
Schetinin and Schult 105]	2004	All	Polynomial network and decision tree	Yes	Clinical Sleep EEG Newborns EEG	No	No
Shoker et al. [29]	2005	Ocular & cardiac	BSS,SVM	Yes	General	No	No
Castellanos and Makarov [88]	2006	All	ICA,Wavelet	Yes	General	No	No
Halder et al. [106]	2007	Ocular and Muscle	ICA, SVM	Yes	BCI	No	Yes
Nazarpour et al. [107]	2008	Ocular	Space time frequency-Robust minimum variance beamformer	Yes	General	Yes	No
Akhtar and James [92]	2009	Focal artifact	ICA, Wavelet	No	General	No	No
Ghandeharion and Erfanian [93]	2010	Ocular	ICA, Wavelet	Yes	General	Yes	No
Chan et al.[108]	2010	Ocular	Adaptive filter - ICA	Yes	General	No	No
Klados et al.[25]	2011	Ocular	Regression and BSS, ICA	Yes	General	No	No
Hsu et al.[97]	2012	Ocular	ICA-wavelet-SVM	Yes	General Single trial EEG	No	No
Vázquez et al. [109]	2012	Ocular, High frequency muscle, cardiac	BSS, Wavelet	Yes	General	Yes	No
Mammone et al. [89]	2012	All	ICA-wavelet	Yes	Multichannel scalp EEG	No	No
Zachariah et al. [90]	2013	All	Wavelet- ICA	Yes	General	No	Yes
Jirayucharoensak and	2013	Ocular	ICA-Lifting wavelet	Yes	General	No	Yes

Article	Year	Artifact type	Method	Automated	Application	Reference channel	Online/ real-time
Israsena [94]							
Cheng et al. [98]	2013	Ocular, Muscle, Cardiac	Adaptive filter with neural network	Yes	General	Yes	Yes
Matsusaki et al.[110]	2013	Ocular	ICA	Yes	General	No	No
Roy et al. [111]	2014	Ocular	Source separation and pattern recognition	Yes	General	Yes	No
Wang et al. [103]	2014	Ocular	ICA, ARX	Yes	General	Yes	No
Hamaneh et al. [112]	2014	Cardiac	ICA-Wavelet	Yes	General Epileptic	No	No
Zhao et al. [113]	2014	Ocular	DWT-Adaptive Predictor Filter	Yes	Portable systems Single channel	No	Yes
Kaur and Singh [91]	2015	All	BSS with ICA –wavelet	Yes	General	No	No
Mahajan and Morshed [95]	2015	Ocular	ICA-Wavelet	Yes	General	No	No
Daly et al. [114]	2015	Ocular & Muscle	Wavelet- ICA-thresholding	Yes	General	No	Yes
Winkler et al. [115]	2015	Ocular	ICA-high pass filtering	Yes	General ERP	No	No
Tavildar and Ashrafi [65]	2016	Motion	MEMD,CCA	Yes	General	No	No
Bono et al. [116]	2016	All	Wavelet packet transform with EMD and wavelet packet transform with ICA	Yes	Pervasive EEG	No	No
Kim et al. [117]	2017	Ocular	ICA-Adaptive filter	Yes	Motor-Imagery	Yes	No
Paradeshi et al. [96]	2017	Ocular	Wavelet- ICA	No	General	No	No
Radüntz et al. [118]	2017	All	ICA-machine learning	Yes	General	No	No
Chavez et al. [119]	2018	Ocular and muscle	Surrogate-based	No	Health care systems with single channel EEG	No	No
Vijayasankar and Kumar [66]	2018	Ocular	EMD-Interval Thresholding	Yes	General	No	No
Barua et al., [120]	2018	All	ICA-wavelet-hierarchical clustering	Yes	Sleep EEG for driver monitoring General	No	Yes
Song and Sepulveda [121]	2018	Muscle	BSS, CCA and ICA	Yes	General	Yes	Yes
Janani et al. [122]	2018	Muscle	BSS,CCA and Spectral-slope rejection	Yes	General Steady-state brain responses	No	No
Cheng et al. [98]	2019	Diverse artifacts	SSA,ICA	Yes	General single-channel	No	No
Liu et al. [67]	2019	Muscle	FMEMD,CCA	Yes	General Few-channel	No	Yes
Richer et al.[123]	2020	Motion and muscle	ICA,CCA	Yes	General EMG	No	Yes
Ahmed et al. [124]	2020	Ocular and power line noise artefacts	Particle swarm optimization and Stone's BSS	Yes	General	Yes	No
Sheela and	2020	Ocular	Filter- ICA- Transient	Yes	General	No	No

Article	**Year**	**Artifact type**	**Method**	**Automated**	**Application**	**Reference channel**	**Online/ real-time**
Puthankattil [125]			artifact reduction		Visual Evoked potential		
Devulapalli et al. [99]	2021	Ocular	FLM with adaptive filtering	Yes	General	No	No
Noorbasha and Sudha [126]	2021	Ocular	SSA,ICA	Yes	General Single Channel	No	Yes
Abidi et al. [100]	2021	Ocular and Muscular	EFICA,TQWT	Yes	General Multi-channel	No	No
Chen et al. [101]	2021	Muscle	VMD,CCA	Yes	General	No	No
Shahbakhti et al. [127]	2021	Ocular	Variation mode extraction and Discrete wavelet transform	Yes	General short segment single channel	No	No
Jamil et al. [128]	2021	Ocular	ICA,DWT	Yes	General Multi-channel	No	No
Dora and Patro [104]	2021	Muscle	SSA,NNR	Yes	General Single-channel	No	No
Trigui, et al. [129]	2021	Ocular	Morphological modeling and orthogonal projection	Yes	General	Yes	No
Chiu et al. [130]	2022	Cardiogenic	Non-linear time-frequency and SVM	Yes	General Single-channel	No	No

4.1Discussion

In this paper, review of physiological artifact removal methods is discussed. The selection of algorithm depends on the BCI application. Most of the methods in the papers provide the comparative analysis using performance metrics like mean square error (MSE), signal-to-noise ratio (SNR), artifact to signal ratio (ASR) etc,. According to the papers considered in our discussion from *Table 4* and *5*, ICA, wavelet and filtering are the most commonly used single artifact removal methods and ICA with wavelet is the most commonly used hybrid artifact removal method. *Figure 9* shows the percentage of algorithms used in the referred papers from *Table 4* and *5*. It depicts 45% of the articles have used hybrid artifact removal methods and remaining are single stage methods. *Figure 10* shows the percentage of hybrid methods used in referred journals from *Table 5*. It illustrates that 41% of referred articles have used ICA-wavelet method making it the highest used method.

BSS-ICA is the most popular single stage artifact removal method and further hybrid methods were developed to increase the efficiency of artifact removal methods. During recent years, hybrid methods are more popular compared to single stage artifact removal methods. Choosing the right algorithm depends on the application as well as on some of the factors like requirement of reference channel, performance of algorithm in artifact removal, manual or automatic processing, real-time/online or offline implementation, single or multi-channel etc.

Most of the methods discussed addresses single-channel EEG data since complexity increases with multi-channel EEG data. ICA is an automatic method and doesn't require reference channel to remove the artifacts but it also has few limitations. It requires visual inspection to automatically identify the IC's with artifacts [131] but when it is combined with statistical components IC's it can be automatically identified [13, 47]. BSS with PCA fails to eliminate the artifact when amplitudes are same [132]. MCA demands that morphology of artifacts to be known. Regression and filtering methods have drawback of requiring reference channel to identify the artifacts [133]. Wavelet transform is also shown as efficient in some of the applications [60, 61], but it fails when there is an overlap of spectral properties and neural activities [133, 134]. Hence, hybrid methods were proposed and these are proved efficient compared to single methods as shown in *Table 5*.

In most of the literature, only ocular or eye blink artifact is considered but there are very limited publications to remove motion or movement artifacts. It is quite challenging to remove movement or motion artifacts but ICA with CCA was shown efficient to remove the motion artifact in [123]. *Figure 11* shows the widely used algorithms for removing physiological artifacts like ocular, cardiac and muscle/motion.

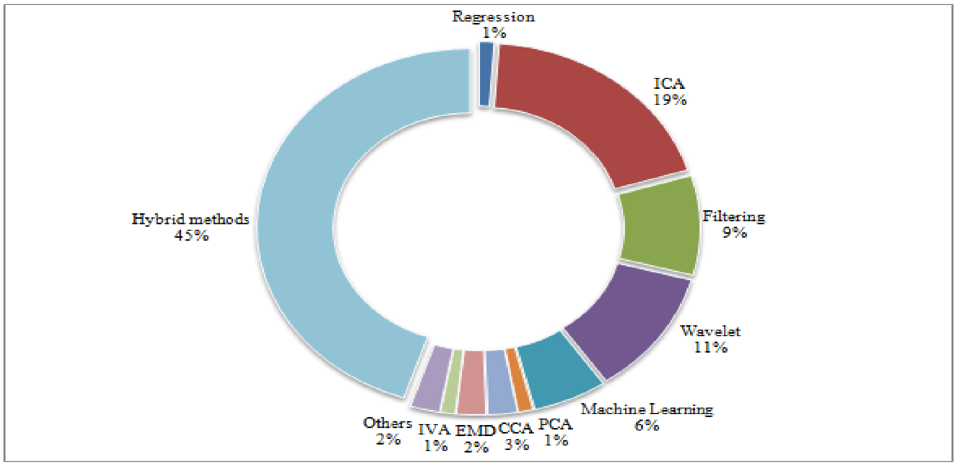

Figure 9 Percentage of algorithms used in recognized journals discussed in this paper

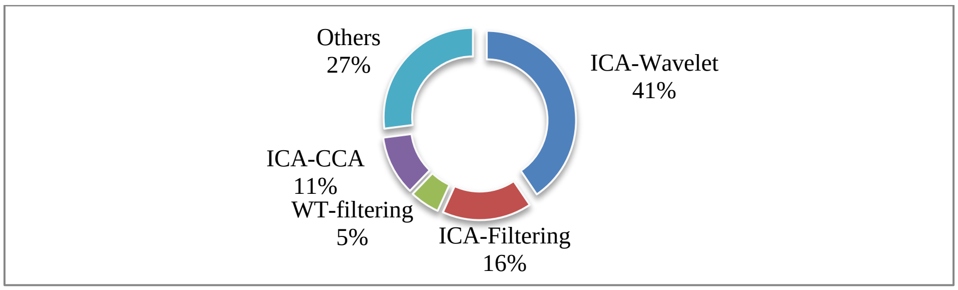

Figure 10 Percentage of hybrid algorithms used in recognized journals discussed in this paper

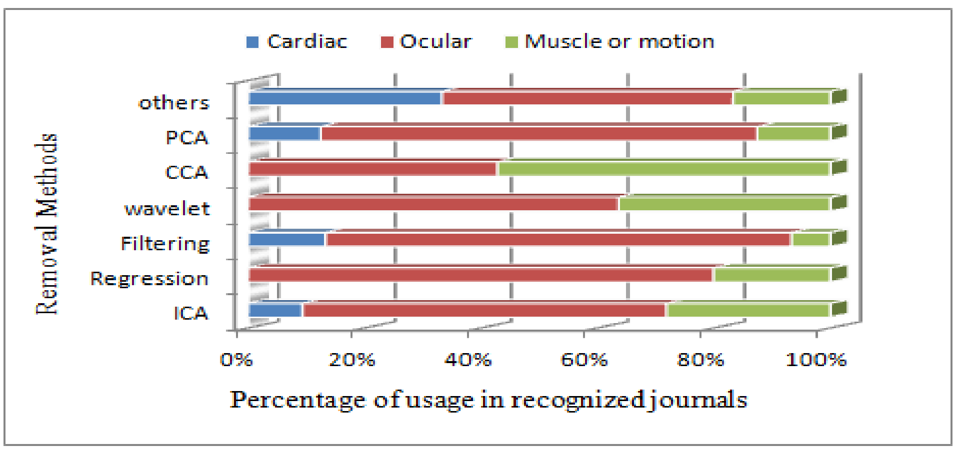

Figure 11 Number of algorithms used for removal of common physiological artifacts such as EMG, ECG or EOG artifacts in recognized publications

4.2Machine learning and deep learning models for artifacts handling

Currently, artifact detection or removal is also addressed using machine learning and deep learning models considering it as hybrid artifact removal methods. SVM combined with other artifact removal technique is the most widely used hybrid method as indicated in [27, 68, 97, 100] , [135−138]. Extreme learning machine algorithm using regression model is proposed in [139] for reducing the cardiac artifact of single channel EEG. K-nearest neighbor (KNN), decision trees and SVM algorithms are used in [140] for detection of artifact and result shows improved precision and recall rate for differentiating contaminated and clean EEG. Adaptive neuro-fuzzy inference with genetic algorithm is proposed in [141] to remove the EOG artifact and a comparative study with Adaptive neuro-fuzzy inference is also shown. Bagged tree ensemble model is used to detect ocular artifact in [142]. Linear regression in combination with continuous wavelet transform is shown in [141] for removal of ECG artifact. Automatic and online EOG artifact removal method called as Deep wavelet sparse autoencoder technique is proposed in [143] and it is considered efficient in comparison with wavelet neural network method for single channel EEG. Deep learning network to remove the ocular artifact is discussed in [144]. Adaptive neural network for cardiac artifact removal with radial basis functional network is used for filter design [145]. Bayesian deep learning technique with independent component analysis is used to classify EEG artifact in [146]. Artifact detector to classify the real artifact using deep learning is shown in [147]; it detects 4 types of artifacts but accuracy of system to be improved. These methods give an evidence to use machine learning or deep learning models to detect or classify the artifacts. But, the accuracy and real-time implementation need to be explored in future for BCI applications.

Convolutional neural networks (CNN) model are more popular now-a-days for identification and classification of EEG artifacts. One dimensional residual CNN (1D-ResCNN) was proposed in [148], it describes the improvement in the root mean square error (RMSE) and signal-to-noise ratio (SNR). This model is also capable of preserving nonlinear properties of the EEG signal. CNN for removal of muscle artifacts is discussed in [149] and showed a promising result to remove the EMG artifact by eliminating the overfitting problem compared to earlier methods. Zhang et al. [150] have demonstrated the use of fully-connected neural network, recurrent neural network (RNN), complex and simple convolutional network and they have shown that these deep learning methods gave good performance in correcting the EEG even with high noise contamination. It is an EEG artifact benchmark dataset called as EEG denoisenet containing clean EEG, ocular and muscle artifact EEG datasets. This system still has few limitations due to time duration of EEG recording which is 2s-long and also the size of dataset to be increased in deep learning applications for better training. Another deep learning method called generative adversarial network (GAN) is also used to remove the ocular artifact as shown in [87]. GAN gave good performance compared to traditional state-of-the-art methods. *Figure 12* shows percentage of machine learning algorithms used to remove the artifacts. It shows that 33% of referred papers have used SVM, 22% have used artificial neural networks and 17% have used deep learning methods. Other methods like KNN, decision trees, Bayesian model etc., are less frequent.

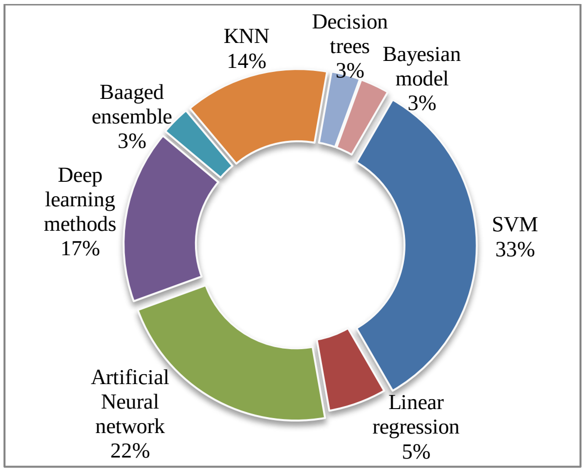

Figure 12 Percentage of machine learning algorithms used in the literature

It can be concluded that, selection of algorithm depends on BCI application and various factors discussed in the previous section. As per the literature, ICA based algorithms can remove all type of artifacts with certain conditions. Regression or filtering can be used only when there is an availability of reference channel. ICA with CCA is better in removing motion or movement artifacts. BSS with wavelet is better for few channel EEG applications. These methods have shown improved SNR and low MSE. Deep learning methods are promising to remove all the artifacts but to be explored more for real time BCI applications. The deep learning methods showed higher SNR and low root mean square error (RMSE) as shown in [148, 128]. Even though there are many methods available, there is no single specific solution for removing all types of artifacts. Hence, it is an open research area where researchers can further try to improve the efficiency and also try to improve the validation techniques for real-time BCI applications.

5.Performance evaluation metrics

It is important to validate the artifact removal method to check the performance of the algorithm. Hence many metrics were used by researchers for validation. Earlier performance evaluation was through visual inspection by experts but it requires neurologists or experts to visualise and it is a time consuming process. Hence other metrics were introduced as shown in *Table 7*. MSE, SNR, RMSE, ASR are the most widely used metrics for validating the algorithms.

MSE gives the difference between true and corrected EEG which is applicable to all the artifacts and it is generally used for simulated EEG data [102]. ASR is the ratio of power of artifact removed from measured EEG to the power of estimated pure EEG which can be used for validation in simulated EEG [143]. RMSE is similar to MSE but it quantifies the amount of information conserved [116]. Relative error (RE) is a time domain metric which computes the error using true EEG and corrected EEG [151].

Mean absolute error (MAE) measures the distortion in frequencies by computing the power spectral density [135]. Mutual information (MI) use joint probability distribution and marginal probability distribution functions and gives the amount of MI between corrected EEG by algorithm and true EEG. All these methods are for simulated EEG and applicable for all types of artifacts. SNR is another popular metric which is most frequently used in validation of EOG and ECG artifact removal methods. It adds EOG to the desired signal with different SNR to validate the performance [131].

Power spectrum is another metric which can be computed to check the inconsistency in spectral density of measured and corrected EEG [152]. This is most common for ocular artifact removal method validation and the advantage of this method is that it can used be for real EEG. Correlation analysis in time domain and visual inspection are the metrics applicable for both real and simulated EEG [153]. The various performance evaluation metrics for real or simulated EEG data are shown in *Table 7.*

Table 7 Performance evaluation metrics for real or simulated EEG data

Performance Metric	**Formula**	**Description**	**Artifact type**	**Real or simulated EEG**
Mean Square Error (MSE) [102]	MSE = $\frac{1}{N}\sum_{i=1}^{N}$ $EEG_{out}(i)$ - $EEG_{in}(i))^2$ where EEG_{out} : Corrected EEG, EEG_{in} : True EEG	Difference between true EEG and Corrected EEG	All	Simulated
R^2 or Artifact to Signal ratio (ASR) [143]	$R^2 = \frac{1}{\sum_{k=1}^{N} e^2(k)} \sum_{k=1}^{N}(d(k) - e(k))^2$ where d(k): Primary or measured signal e(k): error or estimated signal N: number of samples	Ratio of power of artifact removed from measured EEG to the power of estimated pure EEG	All	Simulated
Root Mean square Error (RMSE) [116]	RMSE = $\sqrt{\frac{1}{N}\sum_{i=1}^{N} \mathrm{EEG\,out(i)} - \mathrm{EEGin(i))2}}$ where EEG_{out} : Corrected EEG, EEG_{in} : True EEG	Quantifies the amount of information preserved	All	Simulated
Relative Error (RE) [151]	RE = $\frac{\lvert \mathrm{EEGout} - \mathrm{EEGin} \rvert}{\lvert \mathrm{EEGin} \rvert}$ where EEG_{out} : Corrected EEG, EEG_{in} : True EEG	Time domain metric	All	Simulated
Mean Absolute Error (MAE) [135]	MAE = $\lvert P_{inEEG} - P_{outEEG} \rvert$ Where P: power spectrum density	Measures the distortion in frequency band	All	Simulated
Signal to noise ratio (SNR) [131]	SNR = 10 log $\left[\frac{\sum_{n=1}^{N} s^2(n)}{\sum_{n=1}^{N}(y(n)-\hat{s}(n))^2}\right]$ where s(n): desired artifact free signal $\hat{s}$(n): estimate of s(n) [corrected EEG] y(n): noisy signal, N: number of samples	EOG is added to the desired signal at different SNR	EOG and ECG	Simulated
Mutual Information (MI) [135]	MI = $\iint_{-\infty}^{\infty} f(a,b) \log \frac{f(a,b)}{f(a)f(b)}$ da db where f(a,b) = joint probability distribution function f(a), f(b) =marginal probability distribution	Amount of mutual information between EEG corrected by algorithm and true EEG gives the	All	Simulated

Performance Metric	Formula	Description	Artifact type	Real or simulated EEG
	function	effectiveness of algorithm		
Power spectrum [152]	It is based on auto regressive parametric.	Inconsistency in Power spectral density of measured and corrected EEG is compared	Only ocular	Real
Visual Inspection by Expert [153]	Visual examination	Neurologists or bio-signal expert visual observation	All	Both
Correlation analysis in time domain [153]	Used as a quadratic measure in time domain	Checks the correlation between measured EOG, estimated EOG, measured EEG and corrected EEG	Only Ocular	Both

6.Open source tools and artifact databases

Along with the methods discussed in previous sections, there are few software tools available to automatically remove the artifacts as shown in *Table 8*. *Table 8* describes the techniques supported by each tool. Each toolbox and the artifacts that can be removed are discussed in this section.

6.1Matlab/python plugins and toolboxes for artifact removal

EEGLab

It is an interactive open-source MATLAB toolbox for event-related and continuous EEG, MEG and few electrophysiological data. It supports automatic artifact rejection, filtering that are implemented using ICA method. It allows time-frequency analysis, visualizations, removing bad channels and bad data [154].

FieldTrip

It is Open-source MATLAB toolbox for MEG, EEG, iEEG, NIRS. Its main advantage is that it allows new data format to be added easily and allows user to implement own analysis using MATLAB script. It is able to detect MEG and EOG artifacts with automatic artifact rejection [155].

MEG+EEG analysis & Visualization (MNE)

Open-source software for visualizing, exploring, analyzing neuro-physiological data such as EEG, MEG, sEEG, ECoG,etc. Python is used for implementation. It provides many functions for preprocessing, statistical analysis, visualizations. Automatic bad channel detection and filtering functions can be used for artifact rejection. ICA method is available for artifact rejection in this toolbox [156].

Fully Online and automated artifact removal for brain-computer interfacing (FORCe)

FORCe allows automated artifact removal for BCI applications. Removes eye-blink, movement, ECG and EMG artifacts. It uses wavelet with ICA for removal of artifacts. It is more suitable for online BCI application [109].

High-variance electrode artifact removal algorithm (HEAR)

Hear is open-source algorithm to remove pops and drifts i.e., high-variance electrode artifacts. It supports both online and offline. Electrode variance is used for the detection of artifact [157, 158].

Fully automated statistical thresholding for EEG artifact rejection (FASTER)

FASTER is open-source software for importing data, epoching, re-referencing with few additional operations. In this artifact rejection is based on ICA. Faster has greater than 90% specificity and sensitivity for detection of artifacts [159].

Lagged auto-mutual information clustering (LAMIC)

LAMIC removes artifacts automatically for ERP. It is hybrid implementation with BSS-ICA followed by auto-mutual information [160].

PureEEG

PureEEG provides automatic artifact removal from long-term EEG for epilepsy monitoring. It uses iterative Bayesian estimation scheme [161, 162].

Open-source electrophysiological toolbox (OSET)

OSET is open-source matlab toolbox which uses semi-BSS method for artifact removal. It removes cardiac and EOG artifacts. This toolbox also supports biological signal modelling and processing [163].

Multiple artifact rejection algorithm (MARA)

MARA is Open-source MATLAB based EEGLAB plug-in for artifacts rejection. It uses ICA for artifact removal and also implements supervised learning [164, 165].

Automatic artifact removal (AAR)

AAR is a general-purpose open-source MATLAB based EEGLAB plug-in for artifacts removal. It removes the artifacts using BSS, Spatial filters [166].

An automatic EEG artifact detector based on the joint use of spatial and temporal features (ADJUST)

Adjust is an open-source MATLAB based EEGLAB plug-in for artifact removal from ERP data. It uses ICA for artifact removal [167, 47].

Removing muscle artifacts from EEG (ReMAE)

ReMAE is the new MATLAB toolbox with GUI for removing muscle artifact. It has single channel, multichannel and few channel Denoising modes. GUI makes it user friendly. It implements all the state-of-the-art methods [168].

Table 8 Open-source plug-in and tools for automatic artifact removal

Toolbox	Techniques	Artifact type
EEGLab [154]	• ICA, • Artifact Rejection, • Filtering, • Time/Frequency Analysis, • Event-Related Statistics, • Visualizations	All
FieldTrip [155]	• Time-Frequency Analysis, • Source Reconstruction	MEG, EOG
MNE (MEG+EEG analysis & Visualization) [156]	• ICA, • Connectivity Analysis, • Statistical Analysis • Python Implementation of Pre-Processing Pipeline • Automatic Bad Channel Detection and Interpolation	All
FORCe (Fully Online and automated artifact Removal for brain-Computer interfacing) [109]	• Wavelet decomposition with ICA	Eye-blink, movement, ECG and EMG
HEAR (High-variance Electrode Artifact Removal algorithm) [157, 158]	• Detection depends on electrode variance	Remove pops and drifts i.e., high-variance electrode artifacts
FASTER (Fully Automated Statistical Thresholding for EEG artifact Rejection) [159]	• Artifact rejection based on ICA	All
LAMIC (Lagged auto-mutual information clustering) [160]	• Uses BSS with ICA. Followed by clustering using auto-mutual information	Artifacts for ERP
PureEEG [161, 162]	• Iterative Bayesian estimation scheme	All
OSET (Open-source Electrophysiological Toolbox) [163]	• Semi-BSS	Removes cardiac and EOG artifacts
MARA (Multiple artifact Rejection algorithm) [164, 165]	• ICA • Supervised learning	All
AAR (Automatic artifact removal) [166]	• BSS • Spatial filters etc	All
ADJUST (An automatic EEG artifact detector based on the joint use of spatial and temporal features) [167, 47]	• ICA	Artifacts from ERP
ReMAE (Removing Muscle Artifacts from EEG) [168]	• All state of the art methods	Muscle artifacts

6.2 Open-source EEG artifact datasets

Some of the publicly available open-source EEG artifact datasets are presented in this section. EEG artifact datasets are very limited to public access and most of the researchers don't open-source their datasets. Few available datasets are as follows.

- Real EEG eye artifact dataset available at https://osf.io/2qgrd/
- Semi-simulated EEG/EOG artifact dataset to compare EOG artifact elimination techniques & dataset link is https://data.mendeley.com/datasets/wb6yvr725d/4
- Another dataset called TUH EEG Artifact Corpus (TUAR) contains eye movement, shivering, muscle, chewing, electrode pop, electrode static and lead artifacts. The dataset link is as follows. https://www.isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml
- Movement, EOG, neck and facial EMG for real EEG and it is found at https://github.com/stefan-ehrlich/dataset-automaticArtifactRemoval
- Ocular artifacts such as eye-up movement, eye-blinking, eyebrow movement, eye-left movement and muscle artifacts such as jaw clinch, head movement, jaw movement are available at https://github.com/inabiyouni/EEG_dataset_for_artifact-noise_detection
- A new benchmark dataset called EEGdenoiseNet for deep learning solutions is proposed by Haoming Zhang et al [150]. It contains segments of 4514 clean EEG, 3400 ocular artifact and 5598 muscle artifact. It is available at the following link. https://github.com/ncclabsustech/EEGdenoiseNet. This is the only EEG benchmark dataset available to compare deep learning methods in artifact removal.

These open-source datasets acts as a reference and researchers can easily compare their artifact removal methods with the benchmark datasets.

7.Challenges and recommendations

7.1 Challenges

7.1.1 Need of real-time implementations

Most of the brain computer interface applications like robotic arms, prosthetic arms, and EEG controlled wheelchairs require real-time implementations to bring them into reality. Hence, all these require real-time artifact removal with better accuracy otherwise it will hamper the performance of the system. The key factors for real-time implementations can be accuracy and speed.

Researchers must choose the artifact removal method such that the key factors are not compromised. As per the literature, deep learning models are better in performance but may require more training time. Once trained models are ready, it is the best choice in real-time implementations. Hence, there is a need for more pre-trained deep learning models so that researchers can directly use it to reduce the training time. Other hybrid methods are also good at performance but they may increase the complexity due to the involvement of two or more algorithms.

7.1.2 Need of automated methods

Automated methods are compulsory for real-time applications. As discussed in *Table 4* and *Table 5*, few methods are automated and most of hybrid methods are automated systems depending on the pipeline. Hence, the suitable pipeline should be identified and usage of manual or semi-automated methods like ICA can be avoided at the first stage of pipeline in hybrid methods since bad IC selection is manual in ICA. The selection criteria should also look for reliability and accuracy of the automated method so that manual intervention is eliminated.

7.1.3 Need of reference channel

The artifact removal methods such as regression, adaptive filters require additional reference channel to eliminate the artifact. But, they also pose few challenges due to the noise induced in placement of reference. EOG and ECG reference is used for ocular and cardiac artifact identification respectively. EMG reference is challenging as the signals are dynamic in nature.

Hence, placement of sensors to capture the muscle activities is most significant. Other methods like wavelet transforms and BSS can be used because they don't need reference channel for artifact correction.

7.1.4 Single channel and multi-channel EEG data

The applications such as robotic arms, prosthetics, mind controlled wheelchair, clinical analysis generally use multi-channel EEG as the information gathered from multi-channel is high compared to single channel. But, recently there is an increase in demand for single channel compared to multi-channel because the systems are portable and user-friendly. Single-channel applications are home automation systems, health care, detecting driver drowsiness through EEG etc and these systems demand single channel EEG data. The challenge associated is that the algorithm which gives good performance in single channel may not work well in multichannel and vice-versa. In addition, the performance of the system also depends on the number of channel because multiple electrodes give good performance compared to single electrode. Hence, researchers may inevitably use artifact removal method which works only for single channel EEG in applications which demands portability.

7.1.5 Domain expertise

To bring BCI applications to reality, the domain expertise requirement should be very less so that any user can operate. The manual and semi-automated methods such as systems which need reference channels and ICA's need domain expertise to use the proper reference channel and select the bad IC. Further, the validation process should also be automatic since most systems need visual inspections. Most of the clinical applications need domain expertise to handle the artifacts. But, the BCI systems demand autonomous systems without the need of domain expertise.

7.1.6 Issues in machine learning and deep learning methods

Machine learning and deep learning are most promising methods in recent times to correct the artifacts but they are facing few challenges. The training time taken for deep learning methods is usually more and may require additional computational resources to reduce the training time. In addition, large EEG data is required to train the system for better performance. The difference between machine learning and deep learning methods is in learning process or feature extraction. In machine learning, users know the features but in deep learning methods features are automatically generated which makes learning automatic. To assist the researchers, there is a need of pre-trained models so that users can make use of those models to remove all the artifacts. It is also called as transfer learning.

7.1.7 Need of single artifact removal method for all artifacts

It is one of the open-research area and most challenging task to identify the single artifact removal method which works for all the artifacts. As per the comparison shown in *Table 4* and *5*, there are only few systems identified to remove all the artifacts. Algorithms which require reference channel may work well for cardiac and ocular artifact as ECG and EOG references are available. Single method for EMG artifact is quite challenging as it is more dynamic in nature. Hence, selection of algorithm may depend on the application and type of artifact to be removed.

7.1.8 Requirement of open-source implementations

Open-source implementation helps the researchers to focus on the future work rather than implementing the algorithm from scratch. EEG community has very less open-source implementations and some of the methods like ICA are available in open-source tools or plug-ins but there is no option to test other methods. The advancement of research in other open-source communities is fast compared to EEG community since beginner should invest more time to study and implement. Transfer learning can be incorporated in EEG implementations to aid faster real-time implementations. Recently, few researchers are sharing their work through open science foundation and github tools. Another link to get the papers along with the code is https://paperswithcode.com that gives open-source datasets and benchmarks for analyzing the performance of different methods. These benchmarks are to be increased in future so that beginner can also have a better plan for selection of suitable algorithm.

7.1.9 Need of open-source datasets

The standard publicly available EEG artifact datasets are very limited which makes it difficult to compare the results with the earlier findings. Most researchers don't give access to their datasets like other open-source communities. Also benchmark datasets can be provided to the users so that they can compare the results. Recently, one of the benchmark EEG artifact dataset was proposed in [150] and it is the only available benchmark dataset for deep learning solutions. Some of the available open-source datasets are already discussed in section 6.2.

7.1.10 Challenges in selection of performance evaluation metrics

It is quite challenging to compare the performance of artifact removal method due to the absence of proper validation criterion. Generally, validation can be performed using real or simulated EEG data. When real EEG data is used, it is very difficult to measure noise or EEG signal. This makes it difficult to calculate SNR, ASR, MSE etc. Hence, visual inspection is the most popular method even today to check the performance of the artifact removal algorithm for real EEG data. Another method is to use the simulated EEG signal. It is shown in *Table 6* that most of the metrics are for simulated EEG data. In simulated EEG, the real EEG data is already known so identification of noise becomes easy. Hence, calculation of SNR, ASR, MSE can be done. But the drawback of this method is to simulate EEG data which is exactly the same signal as real EEG. As per the literature, simulated EEG data is for single artifact so comparison with all the artifacts is difficult. Thus, selection of performance metric poses many challenges to researchers and it can be chosen based on the type of EEG data. In addition, there is a need to evaluate the performance for all the artifact removal method if it is a simulated EEG data.

7.2 Recommendations

Researchers should select the artifact removal methods based on the various factors and challenges discussed in section 7.1. For clinical applications, use of reference channel is suggested as domain expertise will be present and only one time, they will use the reference channel. For BCI applications such as robotic arms, wheel chairs, prosthetic arms etc., use of reference channel is an additional overhead since reference channel should be always be connected to the subject. In case of automated applications, use of hybrid automated methods such as wavelet analysis, BSS etc., are suggested and pipeline should be carefully chosen to make it completely automated. Automated methods are very much mandatory for real-time applications and care must be taken in real-time applications to reduce the processing time. If the data size is large, it is better to use deep learning model and keep it pre-trained for future use. This pre-trained model eliminates the training time and further processing can be continued. This process is suitable only if the data size is large because deep learning models require huge dataset for learning the features. Otherwise, use of simple machine learning or hybrid methods is recommended. It is also important to open-source the datasets and implementations to help the researchers for comparison of their results with the previous findings. This may enhance and build the stronger EEG community with good real-time BCI applications.

Among all the methods discussed, Deep learning methods are showing promising results for removal of EOG, ECG and EMG artifacts. CNN model helps to remove the muscle artifact from EEG with better SNR and RMSE [149]. Other methods like RNN, fully connected networks, convolutional networks gave good performance with few limitations discussed in section 4. Hence, deep learning methods are to be explored more for real time artifact removal in BCI applications. In addition, open-source toolbox or plugin with deep learning methods can be developed with user friendly interface. This offers a wide scope in the field of deep learning models to detect and remove the artifacts. Researchers can explore more on hybrid artifact removal methods by integrating deep learning to get better accuracy. A complete list of abbreviations is shown in *Appendix I.*

8.Conclusion

EEG is often contaminated from many sources which lead to inefficient BCI applications. Sources of contamination may be internal or external referred as artifacts. Currently, there are many methods available to remove these artifacts but still it is an open-research topic as the methods are not efficient for removing all the artifacts. This paper provides a systematic review on different methods for physiological artifact removal. It also describes the performance evaluation metrics and some of the open-source tools for automatic removal of artifacts. Since there is no single solution for artifact removal, researchers can focus on the specific application and the necessary factors to improve the performance. In future, efficient validation method and multistage methods can be developed to find the optimal solution for removing all the artifacts.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author’s contribution statement

Rashmi C R: Data collection, interpretation of results, paper writing. **Shantala C P**: Interpretation of results, review and editing.

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Appendix I

S. No.	Abbreviation	Description
1	AAR	Automatic Artifact Removal
2	ADJUST	An automatic EEG Artifact Detector Based on The Joint Use of Spatial And Temporal Features
3	ARX	Auto-Regressive eXogenous
4	ASR	Artifact to Signal Ratio
5	BCI	Brain Computer Interface
6	BSS	Blind Source Separation
7	CCA	Canonical Component Analysis
8	CNN	Convolutional Neural Network
9	CSV	Comma Separated Value
10	DWT	Discrete Wavelet Transform
11	ECG	Electrocardiogram
12	EEG	Electroencephalography
13	EFICA	Efficient Fast Independent Component Analysis
14	EMD	Empirical Mode Decomposition
15	EMG	Electromyography
16	EOG	Electrooculography
17	ERP	Event Related Potential
18	FASTER	Fully Automated Statistical Thresholding for EEG artifact Rejection
19	fGn	Fractional Gaussian Noise
20	FLM	Firefly-Levenberg-Marquardt
21	FMEMD	Fast Multivariate Empirical Mode Decomposition
22	FORCe	Fully Online and automated artifact Removal for brain-Computer interfacing
23	GAN	Generative Adversarial Network
24	HEAR	High-variance Electrode Artifact Removal algorithm
25	ICA	Independent Component Analysis
26	IMF	Intrinsic Mode Function
27	JSON	JavaScript Object Notation
28	KNN	K-Nearest Neighbour
29	LAMIC	Lagged Auto-Mutual Information Clustering
30	OSET	Open-Source Electrophysiological Toolbox
31	MAE	Mean Absolute Error
32	MARA	Multiple Artifact Rejection Algorithm
33	MCA	Morphological Component Analysis
34	MEG	Magnetoencephalography
35	MEMD	Multivariate Empirical Mode Decomposition
36	MI	Multivariate Empirical Mode Decomposition
37	MNE	MEG+EEG analysis & Visualization
38	MSE	Mean Square Error
39	NNR	Neural Network Regressor
40	PCA	Principal Component Analysis
41	RE	Relative Error
42	RMSE	Root Mean Square Error
43	RNN	Recurrent Neural Network
44	RQ	Research Question
45	SNR	Signal to Noise Ratio
46	SSA	Singular Spectral Analysis
47	SSP	Signal Space Projection
48	SVM	Support Vector Machine
49	TMS	Transcranial Magnetic Stimulation
50	TQWT	Tunable Q-factor Wavelet Transform
51	VMD	Variational Mode Decomposition