Biomedical Signal Processing and Control 68 (2021) 102741

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Review of challenges associated with the EEG artifact removal methods

Wajid Mumtaz *, Suleman Rasheed, Alina Irfan

Department of Electrical Engineering, School of Electrical Engineering and Computer Science (SEECS), National University of Sciences and Technology (NUST), Islamabad, Pakistan

ARTICLE INFO

Keywords:
EEG artifact removal method
Independent component analysis
Challenges of artifact removal methods
EEG preprocessing methods
EEG artifact correction methods

ABSTRACT

Electroencephalography (EEG), as a non-invasive modality, enables the representation of the underlying neuronal activities as electrical signals with high temporal resolution. In general, the EEG artifact removal methods have been considered as a fundamental preliminary step during EEG analysis. However, the associated challenges of EEG artifact removal methods should be addressed carefully, to fully utilize the data. This manuscript is based on the notion that the full capacity of the EEG artifact removal methods can be achieved while addressing the associated challenges well. Because these methods could enhance the inferences deduced from the EEG data. The focus of this manuscript is to elaborate challenges (e.g., the algorithm-specific challenges and general challenges) of the EEG artifact removal methods. Considering the challenges, the manuscript has presented recommendations to address them. The manuscript also provides information on Matlab and Python-based toolboxes developed for EEG preprocessing. In addition, this manuscript provides a brief account of the EEG artifact types along with an overview of the EEG artifact removal methods. In short, this manuscript provides information on various EEG artifact removal methods and the recommendations provided serve as guidelines for the selection of suitable tools and methods for EEG artifact corrections.

1. Introduction

Electroencephalography (EEG) has been considered as a standard means to record human brain activity in the form of electric pulses as a function of time. The EEG data have shown great potential as a diagnostic and monitoring tool for various clinical applications such as the quantification of anesthesia levels before/during a surgery [1], the diagnosis of epilepsy [2], and the prediction of occurrence of an epileptic seizure [3], the neurofeedback applications for autistic patients [4] and the neuro-rehabilitation [5]. However, the EEG has been suffering from many inherent challenges such as the removal of the additive noises (i.e., the EEG artifacts) that could be generated by different noise sources such as the muscle movements or due to the electric line interferences. The EEG artifact removal methods are mainly used to clean the artifacts from the EEG data. The success of EEG artifact removal methods enables the full utilization of the EEG data for clinical and industrial applications.

The EEG artifact removal methods have encountered various challenges. These challenges could be either because of the complexity of the methods or could be because of the nonlinearities of the noise being added in the EEG signal. For example, because of the 'nonlinear' nature of the artifacts, it is difficult to extract only the artifacts without the loss of actual neuronal data. In addition, there are methods that could not be used for online applications. The online processing requirements could be imposed by the brain-computer interface (BCI) and neurofeedback applications and preferably for single-channel, which is a challenging condition [6]. Furthermore, the EEG signals are very weak, typically in the 20-mV range, and thus require amplification. However, amplification of the signal leads to an amplification of the artifacts too. These challenges highlight the importance of an artifact handling stage in the EEG signal analysis pipeline that would remove the artifact activity from raw EEG signals while preserving the neuronal activity of the brain [7]. However, the EEG artifact removal methods should overcome the challenges posed by the composite nature of the EEG artifact types.

As explained in Fig. 1, different EEG applications have different requirements of accuracy, speed, reliability, and ease of use of the subject. The trade-offs between these 4 factors would eventually decide which artifact removal algorithm would be most suitable for a particular type of Application. This makes it even harder to select a single EEG artifact removal algorithm as a general best algorithm. For a brief review of different applications of EEG signals, we encourage our readers to read the following papers [8–10]. For Clinical Diagnostic applications (like

* Corresponding author.
E-mail address: wajid.mumtaz@seecs.edu.pk (W. Mumtaz).

https://doi.org/10.1016/j.bspc.2021.102741
Received 4 March 2021; Received in revised form 16 April 2021; Accepted 7 May 2021
Available online 13 May 2021
1746-8094/

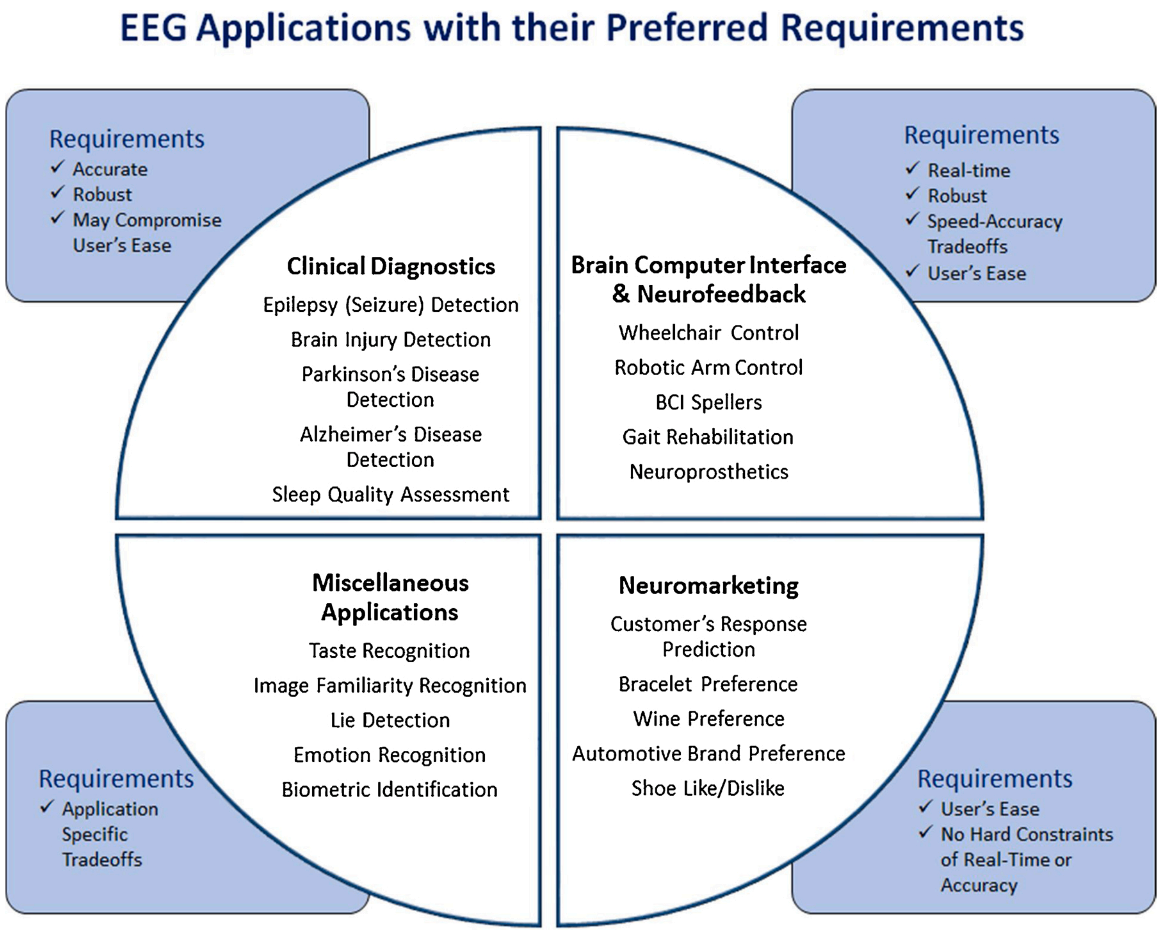

Fig. 1. Different Applications of EEG Signals along with the Desired Requirements. Comments are based on 4 factors only: Accuracy, Robustness, Real-Time, and User's Ease.

Seizure Detection, Alzheimer's Disease Detection, and Brain Injury Detection) the accuracy and reliability of the results outweigh the requirements of speed and user's ease which makes Hybrid methods a very suitable choice. For BCI and Neurofeedback applications (like Wheelchair Control, Exoskeleton Control, and Neuroprosthetics) the speed of the algorithm matters as much as its accuracy, ease of the user, and reliability so practitioners must do a speed-accuracy tradeoff to select an optimal method based on available computational resources and real-time constraints of the application. For Neuromarketing applications (like Customer's Response Prediction, Wine Preference, and Automotive Brand Preference), there are no hard constraints on speed and accuracy and user's ease should be the primary focus. Ease of use

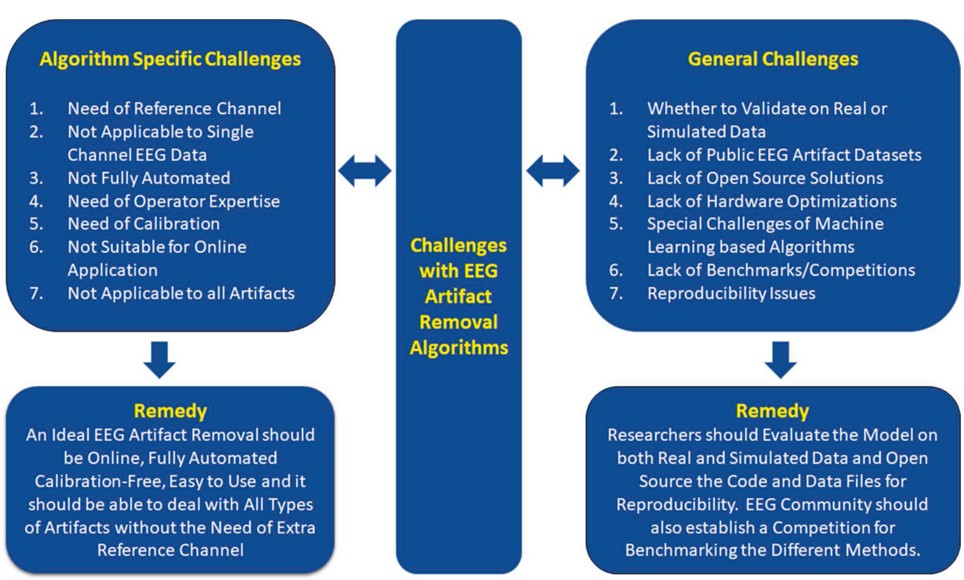

Fig. 2. General and Algorithm Specific Challenges associated with EEG Artifact Removal Algorithms and their Remedy.

means that the overall experiment protocol should be comfortable for the user which suggests that the algorithm should use a minimum number of channels with minimum set up time. This may suggest using algorithms that don't require a lot of calibration and can work well with a small number of channels ideally without the need for a reference channel.

Due to the above-mentioned reasons, it has almost been 50 years since researchers started exploring EEG artifact removal methods, and still to date there is no consensus on which algorithm is optimal for a particular application. Therefore, the researchers must thoroughly study the pros and cons of each of these algorithms from multiple aspects (e.g., automatic vs manual methods, online vs offline methods, suitability for a particular application, etc.) to decide the best choice. The details of these algorithms are beyond the scope of this paper and these excellent review papers can be used as a reference for details: [7,11–14] and [15]. Moreover, there also exists other EEG artifact removal algorithms as well but we have kept the scope of our work to only the most used and well-known EEG artifact removal techniques.

This manuscript has provided a detailed review of different challenges associated with EEG artifact removal algorithms. According to our knowledge, this manuscript is the first of its kind that is solely dedicated to challenges associated with EEG artifact removal algorithms and elaborates both algorithm-specific and general challenges associated with these methods. Most recent reviews [14] and [15] have only discussed different methods and their implementation details. Some older review papers have also discussed some of these challenges as a subsection of their paper or as a few paragraphs in the discussion section and don't cover a wide range of algorithm-specific and general challenges associated with EEG artifact removal algorithms. For example, Jiang et al. [12] and Islam et al. [11] include a discussion on artifact removal algorithms based on only four algorithm-specific challenges; additional reference channel, automatic, online, and applicability to a single EEG channel. Similarly, Mannan et al. [7] discussed different challenges of artifact removal algorithms in the discussion section but a detailed discussion specifically on each of these challenges wasn't in the scope of their work. Eventually, an explicit and detailed discussion on different algorithm-specific and general challenges associated with EEG artifact removal algorithms comes up as a research gap. Therefore, as shown in Fig. 2, the objective of this manuscript is to highlight different challenges of EEG artifact removal methods and provide recommendations on each one of them.

The manuscript has been divided into different sections: section 2 elaborates on different types of artifacts commonly found in the EEG data. Section 3 briefed the artifact removal methods. Sections 4 and 5 talk discuss the algorithm-specific and general challenges of the EEG artifact removal methods. Section 6 gives recommendations for each of these challenges and discusses publicly available Python/MATLAB toolboxes.

2. Different types of artifacts

In general, the EEG signal artifacts may be broadly categorized as physiological and non-physiological artifacts.

1. Physiological Artifacts: These artifacts are also known as internal/intrinsic artifacts and are related to physiological sources of the human body like ocular artifacts (eye blinks and movements), muscle artifacts (muscles movement, jaw/head movement, chewing), and cardiac artifacts (related to heartbeats). These artifacts sometimes may also be referred to as Electrooculogram (EOG), Electromyogram (EMG) and Electrocardiogram (ECG), electrocardiograph (EKG) corresponding to the sensors/techniques that are used to measure these signals.
2. Non-Physiological Artifacts: These artifacts are also known as external/extrinsic artifacts and their sources are related to external factors like environment noise or poor experimentation protocols.

Table 1
A Brief Summary of Artifact Removal Algorithms.

Type	Algorithms	Comments and Citations
Analog Methods	The subtraction of artifacts from the recorded EEG data.	A potentiometer circuitry is used to record and combine artifacts to subtract them from the contaminated EEG records. The popular citations are provided here: [19,20,21,22,23,24]
Regression	Estimation of artifact and subtraction from the EEG data.	Regression-based methods were proposed both for time and frequency domains. Also proposed as an improved version of the analog methods. Popular citations are provided here: [25,26,27,28,29,30,31,32,33]
Adaptive Filtering	LMS, NLMS, RLS, etc	Adaptive filtering suits EEG preprocessing because of the flexible nature of their adaptive transfer function of the filters. The popular citations are provided here: [34,35,36].
BSS	Independent Component Analysis (ICA)	ICA assumes that the data recorded by the surface electrodes is a linear combination of sources inside the brain. Popular citations are provided here: [37,38,39].
BSS	Canonical Correlation Analysis (CCA)	CCA is another BSS method that utilizes correlation to separate different sources of EEG activity. It finds the basis vectors of 2 sets of variables such that the correlation between their projections onto the basis vectors is mutually maximized [7,40,41,42,43,44].
BSS	Principal Component Analysis (PCA)	PCA assumes orthogonality between the brain activities and the artifact sources [45,46]. In case if amplitudes of artifact and neuronal activity are similar then PCA doesn't perform well in separating these types of artifacts [7].
Frequency Decomposition	Wavelet Transform (WT) Decomposition	WT decomposition is mainly based on decomposing the time domain signal to different frequency components utilizing the full capacity of the EEG data and thresholding is applied to identify artifact related components and then the artifact free signal is reconstructed from non-artifactual components only [11,47,48,49,50]
Frequency Decomposition	Empirical Mode Decomposition (EMD)	EMD is mainly a data-driven approach and subjective to individual artifact types. For example, template matching based autodetection and EMD-based artifact removal method [51].
Hybrid Methods	Hybrid methods involve more than one algorithm such as ICA and wavelet decomposition implicated in the wICA method.	The hybrid methods have enjoyed the combined benefits of individual algorithms that implicated a win-win situation. A brief list is cited here.

(continued on next page)

Table 1 (*continued*)

Type	Algorithms	Comments and Citations
		Adaptive filtering and blind source separation (AF-BSS) [52], adaptive filtering and wavelet transform (AF-WT) [53,54], Adaptive Filtering and Empirical Mode Decomposition (AF-EMD) [55], Wavelet Transform and Blind Source Separation (WT-BSS) [56], Empirical Mode Decomposition and Blind Source Separation (EMD-BSS) [57], Blind Source Separation with Support Vector Machines (BSS-SVM) [58,59], etc.

These artifacts include power line noise (50/60 Hz), electrode malfunction (due to floating electrodes such as loose connection with the scalp or high impedance electrodes), electromagnetic interference (due to other electrical devices placed nearby), and variation in impedances due to the slow drying of the conductive paste.

The non-physiological artifacts can be handled well by following strict experimental protocols and precise recording systems augmented with simple, linear filtering (e.g., the notch filter for line noise removal). On the contrary, the physiological artifacts are harder to remove as their spectrum often overlaps with the underlying brain activity, requiring the employment of advanced methods for artifact handling (removal/reduction) [12].

3. EEG artifact removal methods

In the literature, various artifact reduction methods have been proposed. An update on the EEG artifact removal methods can be found in these excellent review articles [14,15]. This section provides a brief account of different categories of the methods. The EEG artifact removal methods can be categorized into general and specific categories. Table 1 provides the specific categories of the methods. On the other hand, the general categories can be made according to different requirements of algorithms e.g., whether the method requires a reference channel or not, single or hybrid methods, etc. These categories help the readers in understanding the different challenges mentioned in the later sections. A list of such categories is provided as follows.

3.1. Reference channel vs non-reference channel methods

The EEG reference channel methods require an extra reference channel to estimate the artifacts. Once the artifacts are identified, a subtraction from the EEG recordings can be done. On the other hand, the non-reference channel methods may perform the decomposition of the raw EEG signals into different components or transform them to another domain so that thresholding can be employed to eliminate artifactual components and then reconstruct the corrected signal using only the remaining components [12]. While the former ones have the advantage of exploiting extra information from the reference channel to estimate artifacts, the latter ones don't need a reference channel, so they are more convenient for the user and have a broader scope.

3.2. Single vs hybrid methods

This categorization is based on how many individual algorithms are involved in the pre-processing pipeline. Popular single methods for EEG artifact removal include Linear Regression, Adaptive Filtering, Wavelet Transform, Blind Source Separation (BSS), and Empirical Mode Decomposition (EMD). On the contrary, the hybrid methods involve a combination of these single methods, e.g., wavelet-based ICA methods [16].

3.3. Single vs multiple channel methods

There could be some situations for which the single-channel methods perform better than the multiple channels such as the EEG-based anesthesia monitoring may need a single-channel artifact removal method. On the other hand, the ICA-based methods could be more suitable for the multiple channel scenarios.

3.4. Offline vs online/real-time methods

The offline scenario may include EEG data recordings for training deep learning architectures e.g., the epileptic EEG records. On the contrary, the neurofeedback applications might need online methods e.g., an autistic patient training during game playing.

3.5. Manual vs automatic methods

The manual methods may include visual inspection of the artifacts and performance of manual deletion. The automatic methods enable auto-detection and auto-correction of the artifacts as is the case with the wICA method [16].

3.6. Linear vs non-linear methods

EEG artifact removal methods may also be categorized as linear and non-linear methods based on how they apply the correction. For example, regression is a linear method while deep learning-based artifact removal methods are non-linear. There is also a scope to explore non-linear analysis-based approaches [17,18] in this regard.

Table 1 provides citations and a brief description of specific types of different artifact removal methods. The interested readers can directly jump to the relevant citations for a detailed description of each method.

4. Algorithm specific challenges

4.1. Requirement of reference channel

The literature has evidenced various methods that require a reference channel to complete the artifact correction, e.g., the analog methods, regression-based methods, adaptive filtering-based methods. These methods exploit the extra information provided by an additional reference channel like EOG/ECG as an estimate of relevant physiological artifacts (ocular, cardiac) and subtract them from the raw EEG data to reduce/remove physiological artifacts.

The requirement of an additional reference channel poses the challenge of handling the placement and extra noise being associated with such a channel. For muscle artifacts, although both the ECG and EMG sensors are good at picking muscle activities, still muscle movements produce very dynamic artifacts. Especially, the EMG sensors must be placed at multiple locations to fully cover these dynamics (as there is no single source of muscle artifacts), which isn't practically feasible. Hence, the artifact removal methods that don't need a reference channel such as the wavelet transform, and the blind source separation algorithms should be the preferred choices for removing the EMG and ECG artifacts. An additional reference channel might create discomfort for the study participants because of the extra gel paste that is applied to the skin before attaching EOG/EMG electrodes.

From the algorithmic point of view, the performance of reference channel dependent algorithms depends upon the robust/correct recording of reference signals. In case, a reference channel malfunctions or because of a loose connection, severe effects on the overall preprocessing pipeline could not be avoided.

The EOG reference channels are normally placed at the Fp1 and Fp2 locations yet they might record the neuronal activities as well and could not serve as pure EOG reference. The methods that use EOG signals as a reference for ocular artifact removal suffer from bidirectional contamination error [60]. These methods assume that the pure EEG signal and EOG signals are uncorrelated which isn't a valid assumption. EEG signals can be contaminated by EOG signals and vice versa and this bidirectional interference would lead towards artifact removal errors. Because the EOG signals might have captured some neuronal activity; therefore, the removal of the EOG also implicated the removal of the neuronal information as well.

4.2. Applicability to single vs multi-channel EEG data

The performance of many EEG artifact removal methods depends upon how many EEG channels or electrodes are used while recording the data. Therefore, it is not necessary for an algorithm that performs well on multi-channel EEG data to perform well on single-channel EEG recordings and vice versa. Ideally, an EEG artifact removal algorithm should be independent of the choice of electrode cap (i.e., number of channels) and should work equally well for a single channel or for multiple EEG channels. However, empirically it has been observed that the performance of certain EEG artifact removal algorithms, especially Blind Source Separation based algorithms like ICA rely heavily on the number of electrodes and they become better at removing artifacts as the number of channels increases. On the contrary, it also has the disadvantage that ICA can't remove artifacts using a single EEG channel. It is also worth mentioning that algorithms like linear regression and adaptive filtering although require an extra reference channel, yet they can be applied to single-channel EEG data effectively.

Multi-channel data has more information than single-channel data but in recent years, single-channel EEG devices have risen in demand and use because of their usability for measurement and their portability. Applications involving clinical diagnostics, prosthetics, wheelchair control, etc. usually involve EEG readings from multiple EEG channels but applications like driver's drowsiness detection or home healthcare application usually involve a single EEG electrode. In these situations, the researchers are bound to use EEG artifact removal algorithms that can work on a single EEG channel.

4.3. Automatic vs manual

Automated methods are always a preferable choice over manual methods unless they compromise the accuracy and reliability of the system. Manual methods of artifact removal may involve visual inspections and deletion of artifact data; the semi-automatic methods may involve both manual and automatic operations. Whereas fully automatic methods don't need human intervention for their processing. The manual intervention makes manual and semi-automated methods relatively time-consuming, and they aren't easily scalable for large EEG datasets. Similarly, for real-time and online applications it is mandatory to use an automated method, so one must be careful about this aspect of the different EEG algorithms as many popular EEG artifact removal algorithms are manual or semi-automatic.

The ICA-based artifact removal is a semi-automated method and may involve two stages: first, it computes independent components (ICs) from the raw EEG data, and then the operator must visualize each of them (using topographic maps and power spectrum) to see which ones correspond to sources other than neural activity e.g., eyes, muscles, etc. and then the second stage involves reconstructing the EEG data from only non-artifact ICs. The second stage requires manual visualization of bad ICs which is an issue towards automation of ICA.

4.4. Expertise of operator

An ideal EEG artifact removal should require minimum user expertise and it should be easy for the operator to use it without in-depth knowledge of the workings of the algorithms.

The performance of the manual or semi-automatic methods depends on the expertise level of the operator. For example, the ICA-based semi-automatic methods could perform better if operated by an expert EEG analyst. The manual step to finding bad independent components (ICs) requires domain expertise and one must visualize the ICs by using topographic maps, power spectrum, and time-domain characteristics to find ICs corresponding to artifacts which is not a trivial job. An expert operator could handle the shortcomings associated with the ICA-based semi-automatic methods.

Moreover, algorithms that need an extra reference channel to remove artifacts demand a higher level of expertise as compared to their alternatives. The operator must be cautious about electrode pop and malfunction errors of the reference channel as any noise introduced via the reference channel would affect the underlying EEG signal as well due to the dependence of the artifact removal algorithm on this channel. In clinical applications, a well-trained person is usually available who can perform manual EEG artifact removal and can take care of the extra channel if applicable. However, for other applications like BCIs, it is always preferable to make the system independent of the expertise of the operator.

4.5. Requirement of calibration

Calibration is the preliminary step of some EEG artifact removal algorithms to fine-tune their parameters or threshold settings. Regression based algorithms require a calibration stage to compute Artifact Propagation Coefficients (Betas) to find the contribution of a noise source from reference channel to different EEG channels. After calibration, these parameters are used to subtract the effect of physiological artifacts from EEG data. Similarly, some automated versions of wavelet analysis-based artifact removal methods require calibration for proper threshold setting.

It should be noted that extra precautions need to be taken during the calibration phase as the parameters learned during the calibration runs would have a direct impact on all the subsequent analyses. Moreover, if an application requires calibration every time, we have to use it then that would be very inconvenient for the end-user.

4.6. Real-time constraints

Neurofeedback and BCIs are among the key applications of EEG that would greatly improve the quality of life of people with motor disabilities. However, these applications demand real-time control without compromising on accuracy. EEG signal artifacts have magnitudes comparable or larger in magnitude than the underlying brain activity that might alter the result of the classification stage of the BCI. As a result, the control command of the wheelchair or prosthetic arm could cause inconvenience for the user. Therefore, accurate artifact removal algorithms that support real-time operations should be considered.

For real-time applications, low latency is almost as important as being accurate, so accuracy-cost trade-offs are made in these scenarios. Regression and Adaptive Filtering are relatively fast, but the requirement of extra channels makes them uncomfortable for the user so despite their low computational cost they aren't usually used in BCI and Neuroprosthetics applications. On the contrary algorithms like EMD and BSS although don't have a reference channel yet are computationally intensive. The researchers must make trade-offs between speed and accuracy. Moreover, In a recent review [7], it has been found that hybrid methods are outperforming single methods and the EEG research community is shifting from single methods to hybrid methods however these methods are a combination of 2 or more single methods that increases the computational complexity.

The *Choice of Programming Language* also directly influences the latency of the final model. MATLAB, Python, and C++ are key

Table 2
Summary of the algorithm-specific challenges.

Method	Need of Reference Channel	Applicable to Single EEG Channel	Expertise of the Operator	Calibration	Fully Automated	Realtime *	Applicable to all types of Artifacts
Regression	*Required* to estimate artifact propagation coefficients (betas)	*Yes*	*Medium* Reference Channel	*Yes* Needed to estimate betas	*Yes* Once calibrated it can work automatically	*Yes*	*No* Theoretically possible, but practically not feasible for muscle artifacts due to unavailability of a single robust EMG reference
Adaptive Filtering	*Required* to estimate noise and subtract it from raw EEG in feedback	*Yes*	Precautions	*No*	*Yes*	*Yes*	
ICA	*Mostly No* A few variants use reference channel for automatic bad Independent Component (IC) rejection	*Not Applicable* Blind Source separation theory based methods assume that the number of artifact sources should at least be equal to number of channels	*High* Manual bad IC selection	*No*	*Mostly No* Manual Bad IC Selection. Some advanced Some variants automate it by adding an additional computational stage	*No*	*Yes*
CCA	*No*		*Easy*	*No*	*Mostly Yes*	*Yes*	*Yes*
PCA	*No*		*Easy*	*No*	Most implementations of these methods use automated thresholding	*Yes*	*Yes*
Wavelet Analysis	*No*	*Yes*	*Easy*	*No*		*No*	*Yes*
EMD	*No*	*Yes*	*Easy*	*No*		*No*	*Yes*
Hybrid **	*Mostly Not Required* Needed only if the first stage algorithm requires a reference channels e.g., regression or adaptive filtering.	*Mostly Yes* Not applicable only if Blind Source Separation (BSS) algorithms are at first stage	*Mostly Easy* Would need reference channel precautions if first stage algorithm requires a reference channel	*Mostly No* Calibration required only if first stage algorithm require calibration e.g., linear regression	*Mostly Yes*	*Mostly No* Extra computational complexity as it is a combination of 2 single methods	*Mostly Yes* Fail for muscle artifacts only If regression or adaptive filtering are first stage algorithms

* Realtime suitability of an algorithm also depends on the available computational resources and hardware specific optimizations. Here we have just given a relative comparison. For practical applications, one should always decide based on their computational requirements.
** For Hybrid Methods exact comments would depend upon the choice of individual methods in the pipeline and the order in which they are applied.

competitors in the domain of EEG-related software development. Python has the advantage of being an easy-to-use high-level programming language which shortens the development time. However, it is much slower than MATLAB and C++ and not the first option for real-time applications. MATLAB and C++ are faster but have very large development time as compared to Python. Moreover, MATLAB also has some great EEG toolboxes, but the biggest issue is that it is not open source. Therefore, one should have a fair understanding of the available computational resources to have an idea of which language should be chosen.

4.7. Different algorithms optimal for different artifact types

An ideal EEG artifact removal algorithm should be able to deal with all types of artifacts. However, it is challenging to use a single method for all types of EEG artifacts. In the past, algorithms were used to remove a particular type of artifact. In recent years, the trend has shifted towards studying artifact removal algorithms that can remove all types of artifacts [7].

Algorithms that need a reference channel are only suitable for ocular and cardiac artifacts as EOG and ECG references give reliable measurements of underlying ocular or cardiac activity. Muscle artifacts can't be practically removed by EMG sensors as they are quite dynamic, and it is really hard to use a single muscle's EMG signal as a true representative of all muscle artifacts. On the other hand, algorithms that don't need a reference channel can theoretically deal with all types of artifacts e.g., ICA is a popular choice in this regard, and it can deal with all types of artifacts. Table 2 provides a summary of the application-specific challenges.

5. General challenges

5.1. Selection of an evaluate criterion

Comparing performances of different EEG artifact removal algorithms seems an important challenge that arises because of the lack of proper validation strategies. In general, the validation may be performed in two ways.

The first approach utilizes real EEG data. From a composite EEG signal, it is difficult to quantify either the pure EEG signal or noise. Hence, it is difficult to compute objective evaluation metrics like signal-to-noise ratio (SNR), Mean Square Error (MSE), etc. Therefore, the most popular way for inspecting the performance of artifact removal algorithms on real EEG data is still by visual inspection. This way of evaluation is neither scalable nor objective measures. Although some researchers have proposed some methods [13] to use objective evaluation measures on real EEG data, there is no consensus on a single approach and visual inspection is still the most popular way of inspecting the performance of artifact removal algorithms on real EEG data.

The second approach is to use synthetic or simulated EEG data. The benefit of this approach is that we know the pure EEG signals and so we can estimate noise from the contaminated signal. Hence, the evaluation metrics like SNR, MSE, etc. can be computed. However, it is hard for the simulated data to be a true representation of actual raw EEG signals. Moreover, most of the simulated datasets used by researchers mostly deal with one type of artifact only which makes it hard to compare algorithms for multiple types of artifacts.

5.2. Lack of open-source EEG artifact datasets

One of the key challenges for researchers developing artifact removal algorithms is that there is no single EEG artifact dataset that is accepted

Table 3
List of Open-Source EEG Artifact Datasets.

Dataset Title	Artifact Types	Nature	Ref	Dataset Link
A semi-simulated EEG/EOG dataset for the comparison of EOG artifact rejection techniques	Ocular	Simulated	[61]	https://data.mendeley.com/datasets/wb6yvr725d/4
EEG eye artifact dataset	Ocular	Real	[62]	https://osf.io/2qgrd/
EEG dataset contaminated with artifact/noise	Ocular, Head/Jaw Movement	Real	–	https://github.com/inabiyouni/EEG_dataset_for_artifact-noise_detection
The TUH EEG Artifact Corpus (TUAR)	5 Types	Real	[63]	https://www.isip.piconepress.com/projects/tuh_eeg/html/downloads.shtml

by the EEG community. Researchers usually use simulated datasets with only a single type of artifact that is not a true representation of actual EEG signals. Others might collect some data under controlled experimental conditions, but they are left with the option of only visual inspection as discussed in the previous section. To make things even harder, most of the time researchers don't open source their artifact datasets so it is really hard to actually compare different algorithms across studies which go back to the issue of reproducibility. Some authors also mention that data can be provided if requested, so one should try to contact them to show interest in their dataset. Table 3 lists some of the open-source EEG Artifact Datasets that we found available for public use.

5.3. Lack of open-source implementations

Among the key barriers in rapid progress in EEG artifact removal techniques is the lack of open-source implementations. Among the key reasons for the rapid development of computer vision algorithms is the availability of open-source and pre-trained object classification, detection, and segmentation algorithms. The benefit of this practice is that researchers don't have to reinvent the wheel and the focus remains on solving their actual problem instead of focusing on writing the code again. Unfortunately, this practice of sharing the code implementations is still not widely adopted in the EEG community. Although some of the popular algorithms like ICA can be found in most of the EEG analysis software/libraries. However, if someone wants to explore other artifact removal algorithms that aren't well known then he/she must have to implement that from the scratch. To make things worse, it is more difficult to integrate a custom algorithm to be a part of an EEG processing pipeline of existing libraries and toolboxes and this integration requires more time and coding effort that could have been used in solving the problem.

5.4. Lack of hardware optimized implementations

Lack of hardware optimized implementations makes it difficult for researchers to transform their EEG-based prototypes into commercial products. Most of the time, when a researcher writes a piece of code in academia then its sole purpose is to demonstrate that proof of a concept of an idea which is the first stage of any product development. However, it is very rare for successful prototypes to go to production as this requires more coding effort to optimize the code for real-world deployment. The commercial viability largely depends upon the choice of cost-effective hardware to implement the code and optimizing the software for that platform is a necessary step in this process. The practice of designing hardware optimized algorithms is usually only adopted by embedded systems developers working in the industry and there is a lack of proper guidance and training in academia in this regard. This gap in software and hardware is often responsible for academic prototypes not being able to create their worth in the market. And the EEG community needs to also focus on optimizing their solutions from hardware aspects.

5.5. Special challenges of machine learning based algorithms

Recently there has been a lot of research done in applications of machine learning especially deep learning in the domain of EEG signal processing. However, the increase in performance comes with an *extra computational cost* and *requirement of large training data* which isn't always a case especially if we talk about brain signals. There is a need to further explore Transfer Learning and Data Augmentation Strategies for EEG signals to deal with data scarcity issues.

Transfer Learning is a technique that uses a pre-trained model trained on a similar task as a baseline and then its parameters are fine-tuned for the new task. This approach helps us train machine learning models in a shorter amount of time with less training data. Unfortunately, transfer learning in EEG signal processing faces a special challenge that the computer vision community didn't have to face. In computer vision tasks, it is easy to resize images to fit the input size of the pre-trained model however, it isn't possible to train an EEG-based model from another model when the electrode cap and configuration of EEG channels aren't exactly identical.

Another way to increase the data synthetically is to apply different data augmentation techniques on the available EEG dataset. For images, it is easy to realize data augmentation strategies like resizing, reshaping, rotation, cropping, flipping, etc. which increase the amount of available training data and so we can extract more insights from the existing dataset. Unfortunately, It is not very easy to realize such transformations for multi-dimensional non-stationary time-series data like EEG.

Deep learning-based methods are often criticized for their *lack of explainability* and often referred to as "Black Box". The main reason is that, unlike traditional algorithms, the feature extraction is automatic so even we may get above 95 % accuracy, we may not know what features are used to arrive at this decision and the model might have memorized unintended and irrelevant information as well that would deteriorate the results in deployment. These papers [64,65] are a good starting for detailed exploration of these issues in deep learning models. Similarly, neural networks are also a hot spot for adversarial attacks [66] as many people try to use some latent feature representation to exploit the weak spots in the deep learning algorithm. So explainable and secure AI is also a big concern.

Moreover, *data privacy and ethics concerns* are much greater for machine learning based methods as we must use data from users to train our machine learning system and people are very sensitive about their data especially when it comes to sharing their brain activity.

5.6. Lack of benchmarks/competitions

One of the main reasons for very fast development in the field of computer vision was the availability of large amounts of open-source datasets that were often a part of a competition. So, whenever a new model is proposed then researchers compare their results on test sets of well-established datasets which makes it easy to benchmark their proposed methods. Unfortunately, in the EEG community, there is no consensus on a single artifact removal dataset as a benchmark which makes it difficult to compare across different models.

Among many other reasons, one of the benefits of competitions/benchmarks is that the train set, and test set are similar for everyone. In literature, one of the worst mistakes of applying machine learning blindly to a new application is to use the same training set for validation/testing, which leads to information leakage so one might get away with publishing his excellent results in reputed venues however, this model would be of no practical use. So, having a consistent and separate

Table 4
Comparison of Popular EEG Artifact Removal Algorithms in Literature.

Study	Year	Type of Artifact	Type of Data	Competing Algorithms	Winners
[67]	2021	Ocular, Muscle, External	Real and Simulated	CCR, AWCCR, ICA, Wavelet ICA	AWCCR (Automatic Wavelet Common Component Rejection)
[68]	2021	Muscle	Real and Simulated	EEMD-ICA, EEMD-CCA, VMD-ICA, VMD-CCA	VMD-CCA (Hybrid, Variational Mode Decomposition-CCA)
[69]	2020	Ocular, Muscle and Movement	Real	WPD based Method, ICA Variants, Wavelet Transform	Wavelet Packet Decomposition (WPD) based Method
[70]	2019	Ocular	Real and Simulated	EAWICA, ICA-W	EAWICA (Wavelet Transform and ICA Hybrid)
[71]	2019	Ocular	Real	ASR, rASR	Riemannian Artifact Subspace Reconstruction (rASR)
[72]	2019	Ocular	Real	ASR, ICA, PCA	Artifact Subspace Reconstruction (ASR)
[73]	2018	Ocular and Muscle	Real and Simulated	SuBAR, Wavelet Thresholding, CCA-EMD	Surrogate based Artifact Rejection (SuBAR)
[74]	2018	Ocular, Muscle	Real and Simulated	BSS-REG (BSS-Regression), ICA, Regression	BSS-REG (Hybrid)
[75]	2018	Ocular, Muscle, and Movement	Real and Simulated	ICA, CCA	Multi-Channel Wiener Filter (MCWF)
[76]	2018	Muscle	Real	Multiple ICA Variants	Extended Infomax based ICA
[77]	2017	Ocular	Real	EYE-REG, EYE-SUB, MARA, EYE-EEG, REGICA	Eye artifact subspace subtraction (EYE-SUB)
[78]	2017	Ocular	Simulated	HMM-AF, ICA	Hidden Markov Model with Adaptive Filtering (HMM-AF)
[79]	2017	Ocular	Real	Eye's Ballistic Physiology based Method (EBPM), ICA Variants	EBPM
[80]	2016	Ocular	Real	ANC Scheme, ICA, ASR	Novel Adaptive Noise Cancellation (ANC) Scheme
[81]	2016	Internal and External	Real	Signal Space Projection (SSP), ICA	tSSP for external artifacts ICA for internal artifacts
[82]	2013	Ocular	Real	NMF, ICA	Non-negative Matrix Factorization (NMF) for fewer EEG Channels
[83]	2012	Muscle	Real and Simulated	ICA, CCA, EMD, WT	EMD for highly contaminated data Different Winners for different levels of contamination
[84]	2011	Ocular	Simulated	Adaptive Filtering, PCA, ICA Variants	ICA SOBI based ICA for real-time
[85]	2009	Ocular	Real	Adaptive Filtering (LMS, RLS), ICA (ex-ICA, SOBI), Time-Varying Adaptive Method	LMS based Adaptive Filtering
[86]	2008	Muscle	Real and Simulated	ICA Variants (AMUSE, SOBI, Infomax, JADE)	AMUSE based ICA
[87]	2007	Ocular	Simulated	Adaptive Filtering, Time Domain Regression	Adaptive Filtering
[60]	2004	Ocular	Real and Simulated	Regression, PCA, ICA	Regression and PCA
[88]	1998	Ocular, Muscle	Real and Simulated	PCA, ICA	ICA

training and test set ensures to overcome this problem. Moreover, if we try too many different settings with the same validation set then this might lead to overfitting the validation set that would not give optimal results on the test set (or real-world deployment).

5.7. Reproducibility issues

Although the lack of open-source data or code is the obvious reason behind reproducibility concerns. However, there is much more to the list. This subsection provides a brief account of these issues.

Reproducibility requires uniformity that can be achieved by promoting uniform data storing methods. Added to the challenge, there is no agreement on a single data storing format and different libraries, and EEG Headset providers output data in different formats. Therefore, it is hard to use some library/framework that is outside the pools of resources provided by the headset manufacturer. Useful research time can be saved if such resources are available and open-sourced.

It is common to observe that the authors might miss providing detailed implementation aspects in their publication. A well-written methodology section should provide a clear view of different modeling and design choices and it should enable its reader to re-implement the same idea. However, this is not the case with most of the research work, and many times researchers don't share things like Which EEG headset and software were used to acquire data? What experiment timing protocols (e.g., cue onset, button press, etc.) were followed? Which library/toolbox was used? Which preprocessing techniques were followed? Which types of features were used? Which data-split strategy was used (random split or k-fold)? How did they perform cross-validation? Which loss function did they choose? What Hyper-parameters optimization was performed? What was the evaluation metric? etc. Without these pieces of information, it is hard for new researchers to re-implement the idea. Table 4 provides a comparison of popular EEG artifact removal algorithms.

6. Discussion

6.1. Recommendations for algorithm specific challenges

'Reference channels' are a feasible choice if we are using EEG

Table 5
Summary Table with respect to methods and algorithm-specific challenges.

Method	Need of Reference Channel	Applicable to Single EEG Channel	Expertise of the operator	Calibration	Automatic	Real-Time	Applicable to all types of artifacts
Regression	Yes	Yes	Medium	Yes	Yes	Yes	No
Adaptive Filtering	Yes	Yes	Medium	No	Yes	Yes	No
ICA	No	No	High	No	No	No	Yes
CCA	No	No	Easy	No	Yes	Yes	Yes
PCA	No	No	Easy	No	Yes	Yes	Yes
Wavelet Analysis	No	Yes	Easy	No	Yes	No	Yes
EMD	No	Yes	Easy	No	Yes	No	Yes
Hybrid	No	Yes	Easy	No	Yes	No	Yes

recordings for a critical task as the extra information provides us more insights related to the artifact and so it is better to use this information to make a robust EEG analysis system. This is the case in clinical diagnostics where the accuracy of the results weighs more than the convenience of the subject and we only need to record the signal once a while, so we don't have to permanently attach these extra electrodes to the user for a long period of time. However, for other applications like prosthetic arm control, wheelchair control, neurofeedback, etc. we must record the brain activity regularly so having an extra electrode always attached to one's head (in case of EOG artifacts) would be very inconvenient.

The '*bidirectional contamination*' error can be handled. One simple solution to this problem is to apply a low-pass filter on the EOG signal before using it as reference [89] which is based on the assumption that most of the high-frequency content in the EOG belongs to EEG signal so removing that would reduce the bidirectional contamination. However, there is no consensus on the threshold frequency of low pass filters and some studies have shown that cerebral artifacts propagate to low-frequency EOG (alpha and beta bands) as well, so simple low pass filtering isn't an optimal solution in that case. To tackle this challenge, Wallstrom et al. [90] utilized an Adaptive Bayesian filtering technique that reduces bidirectional contamination errors substantially and might be a better option if bidirectional contamination must be avoided.

Using a '*simulated/virtual reference channel*' can be an option if someone must apply an EEG artifact removal algorithm that requires a reference channel, and it is not possible/feasible to use an actual reference channel. To simulate EOG activity, we may use EEG signals recorded from prefrontal electrodes FP1 and FP2 as these electrodes show the greatest correlation with EOG activity. However, this might lead to the loss of some underlying neuronal activity captured by these electrodes and might not be an option if we are interested in studying the neuronal activity of the prefrontal cortex. A simulated ECG channel can be obtained if the recorded data also have MEG (magnetoencephalography) signals from a gradiometer or magnetometer. MNE python [91] is an open-source library that has built-in functions to use a simulated channel as a reference for artifact removal and its documentation can be referred to for further implementation details.

Regarding the *'automation'* aspect of Blind Source Separation algorithms, one possible direction is to combine an extra computational stage with the output of ICA to make finding bad Independent Components (ICs) automatic. One of the options is to train a machine learning classifier and apply it to topo maps of ICs to automatically find bad ICs [92,93]. Another option is to combine an ICA with another EEG artifact removal algorithm like wavelet analysis that would make it a hybrid method i.e., wICA [94,95]. However, both these methods also introduce extra computational cost to the overall EEG artifact removal pipeline so this factor should also be considered while automating Blind Source Separation algorithms like ICA.

An ideal EEG artifact removal algorithm shouldn't *'require high expertise of an operator'*. From our understanding, fulfilling this requirement has two prerequisites. First, the method should be fully automated without any manual intervention, so it is easy for the operator to use that method without knowing the detailed working of the underlying technique. Second, the algorithm shouldn't use an extra reference channel to estimate artifact activity. This would avoid extra precautions associated with the reference electrode.

As far as the *'challenge of calibration'* is concerned, exploration of calibration-free methods should be the priority. However, if an algorithm performs good results, then calibration can be an option because it doesn't influence the online operation of the overall pipeline and we just have to compromise the comfort of the user for the gain of accuracy. Linear Regression uses an extra reference electrode for calibration of artifact propagation coefficients so extra precautions associated with the reference electrode should again be considered.

Removal of artifacts from EEG data demands processing power and computational time. This can become an obstacle in '*real-time applications'* where a delay incurred due to pre-processing can be undesirable. For such real-time applications, further modifications to the artifact removal stage can be explored. One of these possibilities is to define a specific frame of EEG data and to run the artifact removal algorithm only on the given frame. This stems from the findings of previous research in EEG signals that analysis of only the initial portion of an EEG signal can provide accurate results [96], motivated by the observation that medical practitioners classify brain signals as normal or abnormal using only the first few minutes of the data. Performing artifact removal on a smaller segment of data would reduce the time and complexity of resources needed before the data is available for the actual application at hand. This can remarkably reduce the processing delay for real-time applications.

Extraction of the first few minutes of the EEG recordings is also promising beyond delay reduction. This can help *reduce the non-physiological artifacts*, because once the EEG electrodes are placed on the scalp, the impedances due to external factors begin to vary with time owing to the gradual drying of the conductive gel. This causes variations in the EEG signal which are not representative of the actual neural activity of the brain. Therefore, the initial segment of the data is hence the most representative of brain activity.

The issue of '*applicability of an algorithm to only a certain type of artifact'* can be resolved by focusing further research on those algorithms that can deal with all types of artifacts ideally without the need for a reference channel. A possible research direction would be to investigate algorithms that don't treat each artifact separately and can differentiate automatically pure EEG from an artifact. For example, Jafari et al. [97] combined ICA with multi-instance learning to classify bad ICs without explicitly labeling all types of artifacts and used all artifacts as a single class. Table 5 provides a summary of the methods and the algorithm specific challenges.

6.2. Recommendations for general challenges

To have a '*uniform and standard evaluation protocol'* for different artifact removal algorithms, [7] suggests a 3-stage evaluation procedure. At the first stage, the algorithms are evaluated on the simulated dataset so that we can compare different algorithms based on objective evaluation measures like Signal to Noise Ratio (SNR). At the second stage, self-recorded real EEG signals should be used to visually analyze the artifact removal performance of the best performing algorithms at the last stage, the algorithms should be evaluated on a standard large EEG database. We believe that this approach can be an ideal protocol for the performance evaluation of artifact removal algorithms.

There is a *'need for a publicly available EEG artifact removal dataset'* that can be used as a benchmark for the evaluation of different artifact removal algorithms. From our findings, Temple University Hospital's TUH EEG Artifact Corpus [63] is the largest public EEG artifact dataset of real clinical EEG recordings with annotations of 5 different types of artifacts and it has the potential to be used as a benchmark for future studies. Recently [98], performed a benchmark study on classifying the artifactual EEG signal to one of these 5 artifact types and this work can be used as a baseline for further work. However, their model only classifies artifacts among one of five types and doesn't repair them. There is a need to evaluate EEG artifact removal algorithms on this dataset.

The EEG community should learn from the data science and machine learning research community who have put a lot of focus on '*the open-source implementations* of the recent articles and it is highly recommended, if not mandatory, for authors to share their code files. It is also encouraged to make well-documented instructions for others who might be interested in their work and might want to reuse their ideas for personal use. Fortunately, the latest publications in the EEG domain often share their code and implementation details which is a good sign for new researchers. Open Science Foundation (https://osf.io/) and Github (https://github.com/) are among the popular tools used by researchers to share their work. Similarly, there are some other initiatives like https://www.paperswithcode.com/ that keep track of machine learning-related research articles whose code is open source and "benchmark" performance of different algorithms on a common dataset. For example, this URL https://paperswithcode.com/sota/eeg-on-seed-iv shows the performance of 4 different papers that used the SEED-IV dataset [99] and compared them with each other. Similarly, mother of all BCI benchmarks (a.k.a moabb) [100] https://github.com/NeuroTechX/moabb is another such initiative that is focused more on BCI related experiments with a goal to build an open-source and comprehensive benchmark of popular BCI algorithms on freely available BCI datasets. So, a beginner may have an idea of which algorithm works best for a dataset and there can be a consensus on how different BCI practitioners report their results.

To have a '*consistency in EEG data storage and data sharing protocols'*, the neuroimaging community has proposed "Brain Imaging Data Structure" BIDS [101] that builds on the idea of the need for a single standard and intuitive way of organizing, storing, and sharing neuroimaging data. The official website https://bids.neuroimaging.io/ has some relevant resources and BIDS compatible datasets can be found on OpenNeuro Website https://openneuro.org/. EEG-BIDS [102] is an extension of the BIDS concept for electroencephalographic (EEG) data and it is encouraged by many researchers to adopt this convention while storing and sharing EEG data. Moreover, famous software platforms like MATLAB and Python also have libraries that can easily import data from BIDS format and so researchers can focus on the analysis part instead of writing scripts for loading data.

There is also a need for *'hardware optimized EEG artifact removal algorithms'*. Fortunately, in recent years, researchers have focused on this research area to make these algorithms suitable for real-time applications. Consider the work of Jafari et al. [97] who combined ICA with a multi-instance learning approach to automate bad ICs selection and then improved the execution speed on embedded hardware from 282 s to 8 s which is quite impressive. Kardon et al. [103] implemented FPGA based custom Canonical Correlation Analysis (CCA) engine for a BCI application and decreased the inference time from microseconds to milliseconds

10 Checkpoints for Reproducible EEG Research

- ❑ Open Source the Code and Data
- ❑ Provide Pseudocode
- ❑ Mention libraries/frameworks/toolboxes used during Analysis
- ❑ Provide Timing Details of the EEG Experiment
- ❑ Mention Preprocessing Steps
- ❑ Follow a Standard (say BIDS) to Store and Share Data.
- ❑ Report Inference Time with Hardware Specifications.
- ❑ Mention the Train-Test Split and Cross Validation Strategy
- ❑ Weak Baselines should be Avoided.
- ❑ Make Comparison with Fine-Tuned Baselines

Fig. 3. To-Do List for Reproducible EEG Research.

with only 1% accuracy degradation. Similarly, Gul et al. [104] implemented a fixed point real-time and online implementation of EMD algorithms on FPGAs. However, these implementations are very specific to a few variants and a few hardware. Future researchers should focus on making hardware optimized implementations of hybrid methods as they are outperforming single methods in terms of accuracy and reliability and if we can implement them for real-time then they could also be used in BCI and Neurofeedback applications like Robotic Arm Control and Wheelchair Control. One should also be careful that these hardware optimized solutions are only desired in real-time EEG applications and are worth exploring only if the EEG artifact removal algorithm is implemented in a real-time EEG application that eventually would lead to commercial products.

'Data Scarcity' is the main concern with machine learning especially deep learning-based EEG artifact removal algorithms. Researchers are exploring options of transfer learning and data augmentation strategies to tackle this challenge. [105] provides an overview of different data augmentation techniques for deep learning-based EEG analysis. There is also an opportunity to further explore unsupervised or semi-supervised algorithms that don't require a lot of training data as compared to supervised techniques. Consider the case of the Automated-ICA algorithm [93] that applies a supervised classifier on the results of the ICA algorithm (i.e., Independent Components) which also need training data for learning. However, Mur et al. [106] recently proposed unsupervised learning based automated and online ICA artifact removal method whose performance was comparable with other state-of-the-art EEG artifact removal algorithms and doesn't require a training dataset.

'High Computational Cost' is also a big concern for deep learning-based methods that make them unsuitable for real-time applications. However, recently a lot of work is done from a hardware-software codesign perspective to optimize the performance of neural networks by utilizing minimum resources in real-time constraints. Azghadi et al. [107] work can be a great starting point to explore biomedical applications of hardware-based neural network accelerators. Moreover, since deep learning based methods do feature extraction automatically so they also shorten the overall pipeline of a typical ML system and so they can still be a good choice depending upon the desired computational requirements of the task at hand.

'Reproducibility' is a hot research topic in the machine learning community and EEG researchers should follow their footsteps towards making their research reproducible. In this regard, we found [108] to be a useful article that has mentioned 10 not-to-do things for Machine Learning researchers while reporting results and most of them are also valid for EEG analysis. Fig. 3 provides a list of 10 'to-do things' for the EEG community to address the reproducibility issues.

6.3. *Popular EEG artifact removal libraries and toolboxes*

This subsection provides a brief account of the '*python-based libraries for automatic removal of artifacts*' for the EEG data. Python, being an open-source and general-purpose programming language, offers several

Table 6
Open Source Matlab-Based EEG Artifact Removal Toolboxes.

Study	Methods
AAR toolbox [109]	Adaptive methods combining EOG as a regressor channel, and BSS methods
ADJUST [110]	ICA methods with objective criterion for selection of artifact-related components
DETECT [111]	Employ Machine learning classification based on AR features that can discriminate the real EEG and from artifacts.
FASTER [112]	such as the variance, mean correlation and spatial kurtosis to detect bad channels in the data. FASTER than applies independent component analysis (ICA)
CORRMAP [113]	the correlation of ICA inverse weights, and finds independent components that are like a user-defined template
SASICA [114]	SASICA is also a didactic tool that allows users to quickly understand what signal features captured by ICs make them likely to reflect artifacts.
FORCe [115]	Combines wavelet transform, ICA and thresholding to implement fully automated and online EEG artifact removal algorithm for BCI applications
HEAR [116]	Removes high variance electrode pop and drift artifacts from EEG data

libraries that are optimized for scientific computation. 'Numpy', 'Scipy', and Matplotlib are backbones of the scientific community in Python. For machine learning and deep learning-based models, Python is the go-to option with 'PyTorch' and 'Tensorflow' as the most popular choices.

If we talk about EEG artifact removal techniques, then typically these algorithms come as a submodule of a larger library. MNE-Python [91] is probably the most widely used library for EEG and MEG analysis. This library has built-in methods for Regression, Independent Component Analysis (ICA) and Signal Space Projection (SSP) based EEG artifact removal. Similarly, 'Scipy' has the standard implementation of Principal Component Analysis (PCA). For deep learning-based models, the braindecode library is also a very good choice that builds upon MNE-Python so these two libraries can easily be integrated into a project.

Although this may not be as exciting as MATLAB toolboxes, however, the most important thing is that a small Google/GitHub search with "[artifact name] code in Python" would lead us to open-source implementations of these algorithms that can easily be used in our own projects. Moreover, Python Package Index (PyPI) is a great online resource for exploring different python libraries and using a keyword like "EEG" or "BCI" would give us all the relevant libraries that were uploaded in the database. There are many other libraries as well related to EEG but here we have only mentioned the most popular ones. One may explore the 'PyPI' website https://pypi.org/ by himself to explore more open-source packages/libraries.

It is also important to note that some of the MATLAB toolboxes also have their equivalents in Python. Moreover, MNE also has a MATLAB and C language interface. Which makes it useful to switch between these libraries.

The '*Matlab-based artifact removal toolboxes*' may help in expediting the implementation of various artifact reduction methods for new researchers. Table 6 provides a summary table of different artifact removal methods.

Declaration of Competing Interest

The authors report no declarations of interest.

References

[1] Y. Park, S.-H. Han, W. Byun, J.-H. Kim, H.-C. Lee, S.-J. Kim, A real-time depth of anesthesia monitoring system based on deep neural network with large EDO tolerant EEG analog front-end, IEEE Trans. Biomed. Circuits Syst. 14 (2020) 825–837, https://doi.org/10.1109/TBCAS.2020.2998172.
[2] J. Thomas, P. Thangavel, W.Y. Peh, J. Jing, R. Yuvaraj, S.S. Cash, R. Chaudhari, S. Karia, R. Rathakrishnan, V. Saini, N. Shah, R. Srivastava, Y.-L. Tan, B. Westover, J. Dauwels, Automated adult epilepsy diagnostic tool based on interictal scalp electroencephalogram characteristics: a six-center study, Int. J. Neural Syst. (2021), 2050074, https://doi.org/10.1142/S0129065720500744.
[3] K. Rasheed, A. Qayyum, J. Qadir, S. Sivathamboo, P. Kwan, L. Kuhlmann, T. O'Brien, A. Razi, Machine learning for predicting epileptic seizures using EEG signals: a review, IEEE Rev. Biomed. Eng. 14 (2021) 139–155, https://doi.org/10.1109/RBME.2020.3008792.
[4] D. Kapgate, Future of EEG based hybrid visual brain computer interface systems in rehabilitation of people with neurological disorders, Int. Res. J. Adv. Sci. Hub. 2 (2020) 15–20, https://doi.org/10.47392/irjash.2020.31.
[5] H. Raza, A. Chowdhury, S. Bhattacharyya, Deep learning based prediction of EEG motor imagery of stroke patients' for neuro-rehabilitation application, in: 2020 Int. Jt. Conf. Neural Netw, IJCNN, IEEE, Glasgow, United Kingdom, 2020, pp. 1–8, https://doi.org/10.1109/IJCNN48605.2020.9206884.
[6] M. Fatourechi, A. Bashashati, R.K. Ward, G. Birch, EMG and EOG artifacts in brain computer interface systems: a survey, Clin. Neurophysiol. 118 (2007) 480–494.
[7] M.M.N. Mannan, M.A. Kamran, M.Y. Jeong, Identification and removal of physiological artifacts from electroencephalogram signals: a review, IEEE Access 6 (2018) 30630–30652, https://doi.org/10.1109/ACCESS.2018.2842082.
[8] X. Gu, Z. Cao, A. Jolfaei, P. Xu, D. Wu, T.-P. Jung, C.-T. Lin, EEG-based Brain-Computer Interfaces (BCIs): A Survey of Recent Studies on Signal Sensing Technologies and Computational Intelligence Approaches and Their Applications, 2020, pp. 1–22.
[9] C.Q. Lai, H. Ibrahim, M.Z. Abdullah, J.M. Abdullah, S.A. Suandi, A. Azman, Literature Survey on Applications of Electroencephalography (EEG), 2018, https://doi.org/10.1063/1.5055472. Penang, Malaysia, p. 020070.
[10] M. Rashid, N. Sulaiman, A.P.P. Abdul Majeed, R.M. Musa, A.F. Ahmad, B.S. Bari, S. Khatun, Current Status, Challenges, and possible solutions of EEG-based brain-computer interface: a comprehensive review, Front. Neurorobot. 14 (2020) 1–36, https://doi.org/10.3389/fnbot.2020.00025.
[11] M.K. Islam, A. Rastegarnia, Z. Yang, Methods for artifact detection and removal from scalp EEG: a review, Neurophysiol. Clin. Neurophysiol. 46 (2016) 287–305, https://doi.org/10.1016/j.neucli.2016.07.002.
[12] X. Jiang, G.-B. Bian, Z. Tian, Removal of artifacts from EEG signals: a review, Sensors 19 (2019) 987, https://doi.org/10.3390/s19050987.
[13] J.A. Urigüen, B. Garcia-Zapirain, EEG artifact removal—state-of-the-art and guidelines, J. Neural Eng. 12 (2015), 031001, https://doi.org/10.1088/1741-2560/12/3/031001.
[14] S. Kotte, J.R.K. Kumar Dabbakuti, Methods for removal of artifacts from EEG signal: a review, J. Phys. Conf. Ser. 1706 (2020), 012093, https://doi.org/10.1088/1742-6596/1706/1/012093.
[15] A. Bisht, C. Kaur, P. Singh, Recent advances in artifact removal techniques for EEG signal processing, in: S. Choudhury, R. Mishra, R.G. Mishra, A. Kumar (Eds.), Intell. Commun. Control Devices, Springer, Singapore, Singapore, 2020, pp. 385–392, https://doi.org/10.1007/978-981-13-8618-3_41.
[16] N.P. Castellanos, V.A. Makarov, Recovering EEG brain signals: artifact suppression with wavelet enhanced independent component analysis, J. Neurosci. Methods 158 (2006) 300–312.
[17] D. Gajic, Z. Djurovic, J. Gligorijevic, S. Di Gennaro, I. Savic-Gajic, Detection of epileptiform activity in EEG signals based on time-frequency and non-linear analysis, Front. Comput. Neurosci. 9 (2015), https://doi.org/10.3389/fncom.2015.00038.
[18] D. Gajic, Z. Djurovic, S. Di Gennaro, F. Gustafsson, Classification of EEG signals for detection of epileptic seizures based on wavelets and statistical pattern recognition, Biomed. Eng. Appl. Basis Commun. 26 (2014), 1450021, https://doi.org/10.4015/S1016237214500215.
[19] J.S. Barlow, A. Remond, Eye movement artifact nulling in EEGs by multichannel on-line EOG subtraction, Electroencephalogr. Clin. Neurophysiol. 52 (1981) 418–423.
[20] J.C. Corby, K. Bs, Differential contributions of blinks and vertical eye movements as artifacts in EEG recording, Psychophysiology 9 (1972) 640–644.
[21] C. Fortgens, M.P.D. Bruin, Removal of eye movement and ECG artifacts from the non-cephalic reference EEG, Electroencephalogr. Clin. Neurophysiol. 56 (1983) 90–96.
[22] D. Girton, J. Kamiya, A simple on-line technique for removing eye movement artifacts from the EEG, Electroencephalogr. Clin. Neurophysiol. 34 (1973) 212–216.
[23] W. McCallum, W. Wg, The effects of attention and distraction on the contingent negative variation in normal and neurotic subjects, Electroencephalogr. Clin. Neurophysiol. 25 (1968) 319–329.
[24] T.W. Picton, S. Bentin, P. Berg, E. Donchin, S.A. Hillyard, R. Johnson, G.A. Miller, W. Ritter, D.S. Ruchkin, M.D. Rugg, M.J. Taylor, Guidelines for using human event-related potentials to study cognition: recording standards and publication criteria, Psychophysiology 37 (2000) 127–152.
[25] R.J. Croft, R.J. Barry, EOG correction of blinks with saccade coefficients: a test and revision of the aligned-artefact average solution, Clin. Neurophysiol. 111 (2000) 444–451.
[26] T. Gasser, L. Sroka, J. Möcks, The correction of EOG artifacts by frequency dependent and frequency independent methods, Psychophysiology 23 (1986) 704–712.
[27] D. Hagemann, E. Naumann, The effects of ocular artifacts on (lateralized) broadband power in the EEG, Clin. Neurophysiol. 112 (2001) 215–231.
[28] S.A. Hillyard, R. Galambos, Eye movement artifact in the CNV, Electroencephalogr. Clin. Neurophysiol. 28 (1970) 173–182.

[29] J.L. Kenemans, P. Molenaar, M.N. Verbaten, S. Jl, Removal of the ocular artifact from the EEG: a comparison of time and frequency domain methods with simulated and real data, Psychophysiology 28 (1991) 114–121.

[30] P.M. Quilter, B. MacGillivray, D. Wadbrook, The removal of eye movement artefact from EEG signals using correlation techniques, Random Signal Anal. IEEE Conf. Publ. 159 (1977) 93–100.

[31] A. Schlögl, C. Keinrath, D. Zimmermann, R. Scherer, R. Leeb, G. Pfurtscheller, A fully automated correction method of EOG artifacts in EEG recordings, Clin. Neurophysiol. 118 (2007) 98–104.

[32] J.L. Whitton, F. Lue, H. Moldofsky, A spectral method for removing eye movement artifacts from the EEG, Electroencephalogr. Clin. Neurophysiol. 44 (1978) 735–741.

[33] J. Woestenburg, M. Verbaten, J. Slangen, The removal of the eye-movement artifact from the EEG by regression analysis in the frequency domain, Biol. Psychol. 16 (1983) 127–147.

[34] C. Beach, M. Li, E. Balaban, A. Casson, Motion Artefact Removal in Electroencephalography and Electrocardiography by Using Multichannel Inertial Measurement Units and Adaptive Filtering, 2021.

[35] S. Selvan, R. Srinivasan, Removal of ocular artifacts from EEG using an efficient neural network based adaptive filtering technique, IEEE Signal Process. Lett. 6 (1999) 330–332.

[36] P. He, G. Wilson, C. Russell, Removal of ocular artifacts from electro-encephalogram by adaptive filtering, Med. Biol. Eng. Comput. 42 (2004) 407–412.

[37] T.-P. Jung, S. Makeig, A.J. Bell, T.J. Sejnowski, Independent component analysis of electroencephalographic and event-related potential data. Cent. Audit. Process. Neural Model, Springer, 1998, pp. 189–197.

[38] S. Makeig, A.J. Bell, T.-P. Jung, T.J. Sejnowski, Independent component analysis of electroencephalographic data, Adv. Neural Inf. Process. Syst. (1996) 145–151.

[39] S. Makeig, T.-P. Jung, D. Ghahremani, T.J. Sejnowski, Independent Component Analysis of Simulated ERP Data, Institute for Neural Computation, University of California, 1996.

[40] W. De Clercq, A. Vergult, B. Vanrumste, W. Van Paesschen, S. Van Huffel, Canonical correlation analysis applied to remove muscle artifacts from the electroencephalogram, IEEE Trans. Biomed. Eng. 53 (2006) 2583–2587.

[41] W. De Clercq, A. Vergult, B. Vanrumste, J. Van Hees, A. Palmini, W. Van Paesschen, S.A. Van Huffel, New muscle artifact removal technique to improve the interpretation of the ictal scalp electroencephalogram, 2005 IEEE Eng. Med. Biol. 27th Annu. Conf. (2006) 944–947.

[42] J. Gao, C. Zheng, P. Wang, Online removal of muscle artifact from electroencephalogram signals based on canonical correlation analysis, Clin. EEG Neurosci. 41 (2010) 53–59.

[43] D.M. Vos, S. Riès, K. Vanderperren, B. Vanrumste, F.-X. Alario, V.S. Huffel, B. Burle, Removal of muscle artifacts from EEG recordings of spoken language production, Neuroinformatics 8 (2010) 135–150.

[44] A. Vergult, W.D. Clercq, A. Palmini, B. Vanrumste, P. Dupont, S.V. Huffel, W. V. Paesschen, Improving the interpretation of ictal scalp EEG: BSS–CCA algorithm for muscle artifact removal, Epilepsia 48 (2007) 950–958.

[45] O.G. Lins, T.W. Picton, P. Berg, M. Scherg, Ocular artifacts in recording EEGs and event-related potentials II: source dipoles and source components, Brain Topogr. 6 (1993) 65–78.

[46] S. Casarotto, A.M. Bianchi, S. Cerutti, C. Ga, Principal component analysis for reduction of ocular artefacts in event-related potentials of normal and dyslexic children, Clin. Neurophysiol. 115 (2004) 609–619.

[47] T. Zikov, S. Bibian, G.A. Dumont, M. Huzmezan, C.R. Ries, A wavelet based de-noising technique for ocular artifact correction of the electroencephalogram, in: IEEEProc. Second Jt. 24th Annu. Conf. Annu. Fall Meet. Biomed. Eng. Soc. Med. Biol., vol. 1, 2002, pp. 98–105.

[48] V. Krishnaveni, S. Jayaraman, N. Malmurugan, A. Kandasamy, D. Ramadoss, Non adaptive thresholding methods for correcting ocular artifacts in EEG, Acad. Open Internet J. 13 (2004).

[49] V. Krishnaveni, S. Jayaraman, L. Anitha, K. Ramadoss, Removal of ocular artifacts from EEG using adaptive thresholding of wavelet coefficients, J. Neural Eng. 3 (2006) 338.

[50] P.S. Kumar, R. Arumuganathan, K. Sivakumar, C. Vimal, Removal of ocular artifacts in the EEG through wavelet transform without using an EOG reference channel, Int. J. Open Probl. Comput. Math. 1 (2008) 188–200.

[51] P.A. Bizopoulos, T. Al-Ani, D.G. Tsalikakis, A.T. Tzallas, D.D. Koutsouris, D. I. Fotiadis, An automatic electroencephalography blinking artefact detection and removal method based on template matching and ensemble empirical mode decomposition, in: 2013 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBC, IEEE, 2013, pp. 5853–5856.

[52] S. Romero, M.A. Mañanas, M.J. Barbanoj, Ocular reduction in EEG signals based on adaptive filtering, regression and blind source separation, Ann. Biomed. Eng. 37 (2009) 176–191.

[53] P.S. Kumar, R. Arumuganathan, K. Sivakumar, C. Vimal, Removal of artifacts from EEG signals using adaptive filter through wavelet transform, in: 2008 9th Int. Conf. Signal Process., IEEE, 2008, pp. 2138–2141.

[54] P.S. Kumar, R. Arumuganathan, K. Sivakumar, C. Vimal, An adaptive method to remove ocular artifacts from EEG signals using wavelet transform, J. Appl. Sci. Res. 5 (2009) 711–745.

[55] X. Navarro, F. Porée, G. Carrault, ECG removal in preterm EEG combining empirical mode decomposition and adaptive filtering, in: 2012 IEEE Int. Conf. Acoust. Speech Signal Process, ICASSP, IEEE, 2012, pp. 661–664.

[56] M.R. Mowla, S.-C. Ng, M.S. Zilany, R. Paramesran, Artifacts-matched blind source separation and wavelet transform for multichannel EEG denoising, Biomed. Signal Process. Control 22 (2015) 111–118.

[57] V. Kamath, Y.-C. Lai, L. Zhu, S. Urval, Empirical mode decomposition and blind source separation methods for antijamming with GPS signals, Proc. IEEEION PLANS 2006 (2006) 335–341.

[58] S. Halder, M. Bensch, J. Mellinger, M. Bogdan, A. Kübler, N. Birbaumer, W. Rosenstiel, Online artifact removal for brain-computer interfaces using support vector machines and blind source separation, Comput. Intell. Neurosci. 2007 (2007).

[59] G. Bartels, L.-C. Shi, B.-L. Lu, Automatic artifact removal from EEG-a mixed approach based on double blind source separation and support vector machine, in: 2010 Annu. Int. Conf. IEEE Eng. Med. Biol., IEEE, 2010, pp. 5383–5386.

[60] G.L. Wallstrom, R.E. Kass, A. Miller, J.F. Cohn, F. Na, Automatic correction of ocular artifacts in the EEG: a comparison of regression-based and component-based methods, Int. J. Psychophysiol. 53 (2004) 105–119.

[61] M. Klados, A Semi-simulated EEG/EOG Dataset for the Comparison of EOG Artifact Rejection Techniques, 2019, https://doi.org/10.17632/WB6YVR725D.4.

[62] Reinmar Kobler, Andreea Sburlea, Catarina Dias, Andreas Schwarz, Valeria Mondini, Gernot Müller-Putz, EEG Eye Artifact Dataset, 2020, https://doi.org/10.17605/OSF.IO/2QGRD.

[63] A. Hamid, K. Gagliano, S. Rahman, N. Tulin, V. Tchiong, I. Obeid, J. Picone, The Temple University Artifact Corpus: An Annotated Corpus of EEG Artifacts, IEEE Signal Process. Med. Biol. Symp. SPMB. 1 (n.d.). https://par.nsf.gov/biblio/10199675.

[64] N. Carlini, C. Liu, Ú. Erlingsson, J. Kos, D. Song, The Secret Sharer: Evaluating and Testing Unintended Memorization in Neural Networks, 2019. ArXiv180208232 Cs. (Accessed 19 November 2020), http://arxiv.org/abs/1802.08232.

[65] C. Song, T. Ristenpart, V. Shmatikov, Machine learning models that remember too Much, in: Proc. 2017 ACM SIGSAC Conf. Comput. Commun. Secur., ACM, Dallas Texas USA, 2017, pp. 587–601, https://doi.org/10.1145/3133956.3134077.

[66] J. Zhang, C. Li, Adversarial examples: opportunities and challenges, IEEE Trans. Neural Netw. Learn. Syst. (2019) 1–16, https://doi.org/10.1109/TNNLS.2019.2933524.

[67] B. Abdi-Sargezeh, R. Foodeh, V. Shalchyan, M.R. Daliri, EEG artifact rejection by extracting spatial and spatio-spectral common components, J. Neurosci. Methods (2021), 109182, https://doi.org/10.1016/j.jneumeth.2021.109182.

[68] Q. Chen, Y. Li, X. Yuan, A hybrid method for muscle artifact removal from EEG signals, J. Neurosci. Methods 353 (2021), 109104, https://doi.org/10.1016/j.jneumeth.2021.109104.

[69] N. Bajaj, J. Requena Carrión, F. Bellotti, R. Berta, A. De Gloria, Automatic and tunable algorithm for EEG artifact removal using wavelet decomposition with applications in predictive modeling during auditory tasks, Biomed. Signal Process. Control 55 (2020), 101624, https://doi.org/10.1016/j.bspc.2019.101624.

[70] M. Val-Calvo, J.R. Álvarez-Sánchez, J.M. Ferrández-Vicente, E. Fernández, Optimization of real-time EEG artifact removal and emotion estimation for human-robot interaction applications, Front. Comput. Neurosci. 13 (2019) 80, https://doi.org/10.3389/fncom.2019.00080.

[71] S. Blum, N.S.J. Jacobsen, M.G. Bleichner, S. Debener, A riemannian modification of artifact subspace reconstruction for EEG artifact handling, Front. Hum. Neurosci. 13 (2019) 141, https://doi.org/10.3389/fnhum.2019.00141.

[72] M. Plechawska-Wojcik, M. Kaczorowska, D. Zapala, The Artifact Subspace Reconstruction (ASR) for EEG signal correction. A comparative study, in: J. Świątek, L. Borzemski, Z. Wilimowska (Eds.), Inf. Syst. Archit. Technol. Proc. 39th Int. Conf. Inf. Syst. Archit. Technol. – ISAT 2018, Springer International Publishing, Cham, 2019, pp. 125–135, https://doi.org/10.1007/978-3-319-99996-8_12.

[73] M. Chavez, F. Grosselin, A. Bussalb, F.D.V. Fallani, X. Navarro-Sune, Surrogate-based artifact removal from single-channel EEG, IEEE Trans. Neural Syst. Rehabil. Eng. 26 (2018) 540–550.

[74] R. Guarnieri, M. Marino, F. Barban, M. Ganzetti, D. Mantini, Online EEG artifact removal for BCI applications by adaptive spatial filtering, J. Neural Eng. 15 (2018), 056009, https://doi.org/10.1088/1741-2552/aacfdf.

[75] B. Somers, T. Francart, A. Bertrand, A generic EEG artifact removal algorithm based on the multi-channel Wiener filter, J. Neural Eng. 15 (2018), 036007, https://doi.org/10.1088/1741-2552/aaac92.

[76] L. Frølich, I. Dowding, Removal of muscular artifacts in EEG signals: a comparison of linear decomposition methods, Brain Inform. 5 (2018) 13–22, https://doi.org/10.1007/s40708-017-0074-6.

[77] Kobler, Reinmar J., Sburlea, Andreea I., Mller-Putz, Gernot R., A Comparison Of Ocular Artifact Removal Methods For Block Design Based Electroencephalography Experiments, (n.d.). https://doi.org/10.3217/978-3-85125-533-1-44.

[78] M. Mohammadpour, V. Rahmani, A hidden markov model-based approach to removing EEG artifact, in: 2017 5th Iran. Jt. Congr. Fuzzy Intell. Syst. CFIS, IEEE, Qazvin, Iran, 2017, pp. 46–49, https://doi.org/10.1109/CFIS.2017.8003655.

[79] S. Zhang, J. McIntosh, S.M. Shadli, P.S.-H. Neo, Z. Huang, N. McNaughton, Removing eye blink artefacts from EEG—a single-channel physiology-based method, J. Neurosci. Methods 291 (2017) 213–220, https://doi.org/10.1016/j.jneumeth.2017.08.031.

[80] A. Kilicarslan, R.G. Grossman, C.-V. Jl, A robust adaptive denoising framework for real-time artifact removal in scalp EEG measurements, J. Neural Eng. 13 (2016), 026013.

[81] N.T. Haumann, L. Parkkonen, M. Kliuchko, P. Vuust, E. Brattico, Comparing the performance of popular MEG/EEG artifact correction methods in an evoked-response study, Comput. Intell. Neurosci. 2016 (2016) 1–10, https://doi.org/10.1155/2016/7489108.
[82] C. Damon, A. Liutkus, A. Gramfort, S. Essid, Non-negative matrix factorization for single-channel EEG artifact rejection, in: 2013 IEEE Int. Conf. Acoust. Speech Signal Process., IEEE, Vancouver, BC, Canada, 2013, pp. 1177–1181, https://doi.org/10.1109/ICASSP.2013.6637836.
[83] D. Safieddine, A. Kachenoura, L. Albera, G. Birot, A. Karfoul, A. Pasnicu, A. Biraben, F. Wendling, L. Senhadji, I. Merlet, Removal of muscle artifact from EEG data: comparison between stochastic (ICA and CCA) and deterministic (EMD and wavelet-based) approaches, EURASIP J. Adv. Signal Process. 2012 (2012) 127, https://doi.org/10.1186/1687-6180-2012-127.
[84] E. Kroupi, A. Yazdani, J.-M. Vesin, T. Ebrahimi, Ocular artifact removal from EEG: a comparison of subspace projection and adaptive filtering methods, in: 2011 19th Eur. Signal Process. Conf., IEEE, 2011, pp. 1395–1399.
[85] M.A. Klados, C. Papadelis, C.D. Lithari, P.D. Bamidis, The removal of ocular artifacts from EEG signals: a comparison of performances for different methods, in: J. Vander Sloten, P. Verdonck, M. Nyssen, J. Haueisen (Eds.), 4th Eur. Conf. Int. Fed. Med. Biol. Eng., Springer, Berlin Heidelberg, Berlin, Heidelberg, 2009, pp. 1259–1263, https://doi.org/10.1007/978-3-540-89208-3_300.
[86] M. Crespo-Garcia, M. Atienza, Jose L. Cantero, Muscle artifact removal from human sleep EEG by using independent component analysis, Ann. Biomed. Eng. 36 (2008) 467–475.
[87] P. He, G. Wilson, C. Russell, M. Gerschutz, Removal of ocular artifacts from the EEG: a comparison between time-domain regression method and adaptive filtering method using simulated data, Med. Biol. Eng. Comput. 45 (2007) 495–503, https://doi.org/10.1007/s11517-007-0179-9.
[88] T.-P. Jung, C. Humphries, T.-W. Lee, S. Makeig, M.J. McKeown, V. Iragui, T. J. Sejnowski, Removing electroencephalographic artifacts: comparison between ICA and PCA, Neural Netw. Signal Process. VIII (1998) 63–72.
[89] T. Gasser, P. Ziegler, W.F. Gattaz, The deleterious effect of ocular artefacts on the quantitative EEG, and a remedy, Eur. Arch. Psychiatry Clin. Neurosci. 241 (1992) 352–356.
[90] G.L. Wallstrom, R.E. Kass, A. Miller, J.F. Cohn, N.A. Fox, Correction of ocular artifacts in the EEG using bayesian adaptive regression splines, in: C. Gatsonis, R. E. Kass, A. Carriquiry, A. Gelman, D. Higdon, D.K. Pauler, I. Verdinelli (Eds.), Case Stud. Bayesian Stat., Springer, New York, New York, NY, 2002, pp. 351–365, https://doi.org/10.1007/978-1-4612-2078-7_19.
[91] A. Gramfort, MEG and EEG data analysis with MNE-Python, Front. Neurosci. 7 (2013), https://doi.org/10.3389/fnins.2013.00267.
[92] S. Halder, M. Bensch, J. Mellinger, M. Bogdan, A. Kübler, N. Birbaumer, W. Rosenstiel, Online artifact removal for brain-computer interfaces using support vector machines and blind source separation, Comput. Intell. Neurosci. 2007 (2007).
[93] T. Radüntz, J. Scouten, O. Hochmuth, B. Meffert, Automated EEG artifact elimination by applying machine learning algorithms to ICA-based features, J. Neural Eng. 14 (2017), 046004, https://doi.org/10.1088/1741-2552/aa69d1.
[94] N. Mammone, F. La Foresta, F.C. Morabito, Automatic artifact rejection from multichannel scalp EEG by wavelet ICA, IEEE Sens. J. 12 (2012) 533–542, https://doi.org/10.1109/JSEN.2011.2115236.
[95] C.Y. Sai, N. Mokhtar, H. Arof, P. Cumming, M. Iwahashi, Automated classification and removal of EEG artifacts with SVM and Wavelet-ICA, IEEE J. Biomed. Health Inform. 22 (2018) 664–670, https://doi.org/10.1109/JBHI.2017.2723420.
[96] S. López, I. Obeid, J. Picone, Automated Interpretation of Abnormal Adult Electroencephalograms, Temple Univ, 2017. MS Thesis.
[97] A. Jafari, S. Gandhi, S.H. Konuru, W. David Hairston, T. Oates, T. Mohsenin, An EEG artifact identification embedded system using ICA and multi-instance learning, Proc. - IEEE Int. Symp. Circuits Syst. (2017) 1–4, https://doi.org/10.1109/ISCAS.2017.8050346.
[98] S. Roy, Machine Learning for Removing EEG Artifacts: Setting the Benchmark, 2019, pp. 5–6.
[99] W.-L. Zheng, W. Liu, Y. Lu, B.-L. Lu, A. Cichocki, EmotionMeter: A Multimodal Framework for Recognizing Human Emotions, IEEE Trans. Cybern. 49 (2019) 1110–1122, https://doi.org/10.1109/TCYB.2018.2797176.
[100] V. Jayaram, A. Barachant, MOABB: trustworthy algorithm benchmarking for BCIs, J. Neural Eng. 15 (2018), 066011, https://doi.org/10.1088/1741-2552/aadea0.
[101] K.J. Gorgolewski, T. Auer, V.D. Calhoun, R.C. Craddock, S. Das, E.P. Duff, G. Flandin, S.S. Ghosh, T. Glatard, Y.O. Halchenko, D.A. Handwerker, M. Hanke, D. Keator, X. Li, Z. Michael, C. Maumet, B.N. Nichols, T.E. Nichols, J. Pellman, J.-B. Poline, A. Rokem, G. Schaefer, V. Sochat, W. Triplett, J.A. Turner, G. Varoquaux, R.A. Poldrack, The brain imaging data structure, a format for organizing and describing outputs of neuroimaging experiments, Sci. Data 3 (2016), 160044, https://doi.org/10.1038/sdata.2016.44.
[102] C.R. Pernet, S. Appelhoff, K.J. Gorgolewski, G. Flandin, C. Phillips, A. Delorme, R. Oostenveld, EEG-BIDS, an extension to the brain imaging data structure for electroencephalography, Sci. Data 6 (2019) 103, https://doi.org/10.1038/s41597-019-0104-8.
[103] R. Karkon, S.M. Reza Shahshahani, H.R. Mahdiani, A Custom Hardware CCA Engine for Real-time SSVEP-based BCI Applications, 2020, pp. 1–6, https://doi.org/10.1109/cads50570.2020.9211863.
[104] S. Gul, M.F. Siddiqui, N. Ur Rehman, FPGA based real-time implementation of online EMD with fixed point architecture, IEEE Access 7 (2019) 176565–176577, https://doi.org/10.1109/ACCESS.2019.2957819.
[105] E. Lashgari, D. Liang, U. Maoz, Data augmentation for deep-learning-based electroencephalography, J. Neurosci. Methods 346 (2020), 108885, https://doi.org/10.1016/j.jneumeth.2020.108885.
[106] A. Mur, R. Dormido, N. Duro, An unsupervised method for artefact removal in EEG signals, Sensors 19 (2019) 2302, https://doi.org/10.3390/s19102302.
[107] M.R. Azghadi, C. Lammie, J.K. Eshraghian, M. Payvand, E. Donati, B. Linares-Barranco, G. Indiveri, Hardware Implementation of Deep Network Accelerators Towards Healthcare and Biomedical Applications, 1, 2020, pp. 1–21.
[108] F. Minhas, A. Asif, A. Ben-Hur, Ten Ways to Fool the Masses With Machine Learning, ArXiv190101686 Cs Stat, 2019. http://arxiv.org/abs/1901.01686.
[109] G. Gómez-Herrero, Automatic Artifact Removal (AAR) Toolbox v1. 3 (Release 09.12. 2007) for MATLAB, Tampere University of Technology, 2007.
[110] A. Mognon, J. Jovicich, L. Bruzzone, M. Buiatti, ADJUST: an automatic EEG artifact detector based on the joint use of spatial and temporal features, Psychophysiology 48 (2011) 229–240.
[111] V. Lawhern, W.D. Hairston, K. Robbins, DETECT: a MATLAB toolbox for event detection and identification in time series, with applications to artifact detection in EEG signals, PLoS One 8 (2013) e62944.
[112] H. Nolan, R. Whelan, R. Reilly, FASTER: fully automated statistical thresholding for EEG artifact rejection, J. Neurosci. Methods 192 (2010) 152–162.
[113] F.C. Viola, J. Thorne, B. Edmonds, T. Schneider, T. Eichele, S. Debener, Semi-automatic identification of independent components representing EEG artifact, Clin. Neurophysiol. 120 (2009) 868–877.
[114] M. Chaumon, D.V. Bishop, B. Na, A practical guide to the selection of independent components of the electroencephalogram for artifact correction, J. Neurosci. Methods 250 (2015) 47–63.
[115] I. Daly, R. Scherer, M. Billinger, G. Muller-Putz, FORCe: fully online and automated artifact removal for brain-computer interfacing, IEEE Trans. Neural Syst. Rehabil. Eng. 23 (2015) 725–736, https://doi.org/10.1109/TNSRE.2014.2346621.
[116] R.J. Kobler, A.I. Sburlea, V. Mondini, G.R. Müller-Putz, HEAR To Remove Pops and Drifts: the High-variance Electrode Artifact Removal (HEAR) Algorithm, ArXiv190712354 Eess, 2019. http://arxiv.org/abs/1907.12354.