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COMPREHENSIVE REVIEW/REVUE GÉNÉRALE

Methods for artifact detection and removal from scalp EEG: A review

Les méthodes de détection et de rejet d'artefact de l'EEG de scalp : revue de littérature

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Scalp EEG;
Wavelet transform

Summary Electroencephalography (EEG) is the most popular brain activity recording technique used in wide range of applications. One of the commonly faced problems in EEG recordings is the presence of artifacts that come from sources other than brain and contaminate the acquired signals significantly. Therefore, much research over the past 15 years has focused on identifying ways for handling such artifacts in the preprocessing stage. However, this is still an active area of research as no single existing artifact detection/removal method is complete or universal. This article presents an extensive review of the existing state-of-the-art artifact detection and removal methods from scalp EEG for all potential EEG-based applications and analyses the pros and cons of each method. First, a general overview of the different artifact types that are found in scalp EEG and their effect on particular applications are presented. In addition, the methods are compared based on their ability to remove certain types of artifacts and their suitability in relevant applications (only functional comparison is provided not performance evaluation of methods). Finally, the future direction and expected challenges of current research is discussed. Therefore, this review is expected to be helpful for interested researchers who will develop and/or apply artifact handling algorithm/technique in future for their applications as well as for those willing to improve the existing algorithms or propose a new solution in this particular area of research.

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MOTS CLÉS
Analyse en composantes indépendantes ;
EEG ambulatoire ;
EEG de scalp ;
Interface cerveau-machine ;
Mode de décomposition empirique ;
Rejet d'artefact ;
Transformation en ondelettes

Résumé L'électroencéphalographie (EEG) est une technique d'exploration du cerveau très utilisée dans une large gamme d'applications. L'un des problèmes couramment rencontrés dans les enregistrements EEG est la présence d'artefacts qui viennent de sources autres que l'activité cérébrale et contaminent significativement les signaux acquis. En conséquence, de nombreux travaux de recherche ont été effectués depuis les années 2000 pour identifier les moyens d'éliminer ces artefacts dans une étape de prétraitement du signal. Ceci est toujours l'objet de recherches actives, car aucune méthode existante de détection et rejet d'artefacts n'est parfaite et n'a pu faire l'objet d'un consensus. Cet article présente une revue détaillée et un état de l'art concernant les méthodes de détection et rejet d'artefacts à partir des enregistrements EEG de scalp pour toutes les applications potentielles basées sur l'EEG et analyse les avantages et les inconvénients de chaque méthode. Tout d'abord, un aperçu général des différents types d'artefacts qui peuvent s'observer dans l'EEG de scalp et leur impact en fonction d'applications particulières sont présentées. Puis, les méthodes sont comparées en fonction de leur capacité à éliminer certains types d'artefacts et de leur valeur dans les différentes applications pertinentes (seule une comparaison « fonctionnelle » est présentée et non l'évaluation de la performance de ces méthodes). Enfin, les orientations futures et les défis des recherches actuelles sont discutées. Cette revue devrait être utile pour les chercheurs intéressés à développer et/ou à appliquer des algorithmes ou techniques de manipulation d'artefacts EEG dans leurs travaux futurs, ainsi que pour ceux qui souhaitent améliorer les algorithmes existants ou de proposer de nouvelles solutions dans ce domaine de recherche spécifique.

Introduction

Electroencephalography (EEG) is a non-invasive recording technique that measures the electrical activity of brain by placing electrodes on the scalp [65]. Due to its non-invasiveness and cost-benefit ratio, EEG has been the most preferred method of brain recording in clinical studies, lab experiments, patient health monitoring [36], diagnosis and many other applications. Unfortunately, EEG recordings are often contaminated by different forms of artifacts, such as artifacts due to electrode displacement, motion artifacts, ocular artifacts and EMG artifacts from muscle activity. These offending artifacts not only misinterpret the underlying neural information processing but may also themselves be difficult to identify. For example, during patient monitoring in a critical care unit or during epilepsy seizure detection, artifacts may increase the chance of false alarms [26,84]. Another example is during brain-computer interface (BCI) applications, where artifacts can modify or alter the shape of a neurological event (e.g. event-related potential or ERP) that drives the BCI system and that eventually results in an unintentional control of the device [100]. The same problem may occur during sleep study [82] and diagnosis of other neurological disorders such as Alzheimer's disease (AD) [13], schizophrenia [95], etc. Therefore, artifact detection and removal is one of the most important preprocessing steps for neural information processing applications.

The variety of artifacts and their overlap with signals of interest in both spectral and temporal domains, even sometimes in the spatial domain, makes it difficult for simple signal preprocessing technique to identify them from EEG. Therefore, the use of simple filtering or amplitude thresholds to remove artifacts often results in poor performance both in terms of signal distortion and artifact removal. So far, a large number of methods/algorithms have been developed for artifact detection and removal from EEG signals. However, as we will discuss in this paper, there is no universal complete solution yet available for this particular problem. More specifically, a careful review of the relevant artifact detection removal algorithms/methods reveals that there is a gap between designed algorithm and its target application. Most of the available techniques are not application-specific and therefore unnecessary computational burden arises.

Considering this issue, this paper aims to provide a comprehensive survey on the existing state-of-the-art artifact detection and removal methods from scalp EEG for all potential EEG-based applications. It is worthy to note that this research deals with artifacts and their handling methods found only in scalp EEG recordings, not stimulation artifacts or artifacts found in simultaneous EEG-fMRI recordings. There are several useful algorithms proposed in the literature to remove artifacts from such EEG-fMRI signals, such as [2,3,25]. Interested researchers can take a look at these references for more information. In addition, since currently there is no universal standard quantitative metric available for performance evaluation of existing artifact removal methods,[1] this paper does not report such performance evaluation, but rather provides only the functional comparison between methods.

To this end, first we briefly introduce typical artifact types that are found in scalp EEG. Then, we provide a comparative analysis of the existing methods/algorithms with their advantages, limitations and application-specific challenges. Finally, the future direction is discussed to provide application-specific solutions with reasonable complexity, optimized performance and most importantly with feasible

[1] There are a couple of articles [39,52] that proposed to use simulated EEG data for performance evaluation of any artifact removal method in a quantitative manner. Interested readers who wish to explore the quantitative performance evaluation technique of any artifact removal method are requested to consult the mentioned articles for more details.

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solutions. We believe that this review paper can help researchers to choose the most suitable artifact handling method for a particular EEG-based application. Moreover, it would also be useful for those researchers interested in designing and implementing new methods/algorithms to handle artifacts in a more efficient way, keeping in mind the particular application.

A list of symbols and notations commonly used in this paper is shown in Table 1.

The rest of this paper is organized as follows. Section ''EEG and artifact characterization'' introduces typical EEG and artifact characteristics. Section ''Existing artifact handling methods'' briefly describes the mechanism of all the existing methods for artifact detection and removal. Section ''Comparison between methods'' provides a comparative analysis between the methods and their suitability for different applications. Section ''Discussion'' discusses the current status of artifact handling software plug-ins and also provides future directions of this research. Finally, section ''Conclusions'' gives concluding remarks.

EEG and artifact characterization

EEG characteristics

EEG is the recording of the electrical activities from surface/scalp of the brain and typically described in terms of rhythms and transients. The rhythmic activity of EEG is divided into bands of frequency. Although the common EEG rhythms are delta, theta, alpha and beta waves, however, recently the gamma wave comes into EEG analysis in certain cases. Moreover, mu wave is also considered as a variant because of lack of association with dysfunction or diseases. The corresponding frequency bands of these waves are given in Table 2.

Artifacts

EEG recordings are often contaminated by different forms of artifacts. The artifacts in EEG recording are of various types that come from different sources. In broad sense, artifacts in EEG can be originated from internal and external sources and contaminate the recordings in both temporal and spectral domains with wide frequency band. Internal source of artifacts are due to physiological activities of the subject (e.g. ECG, EMG/muscle artifacts, EOG) and its movement. External source of artifacts are environmental interferences, recording equipment, electrode pop-up and cable movement. Also some artifacts may present in several neighboring channels (global) while some of them can be found only in single-channel (local). In addition, some artifacts appear as regular periodic events such as ECG or pulse artifacts (regular/periodic) while some others may be extremely irregular. An example of artifact-contamination is illustrated in Fig. 1.

A summary of different artifact types and their origins is provided in Table 3.

Table 1 Description of notations. Q9

Symbol	Description
TVD	Total variation de-noising
EIH	Energy interval histogram
EAS	Ensemble average subtraction
PWC-PSVM	Probabilistic SVM with pairwise coupling
APF	Adaptive predictor filter
OPTIMI	Online predictive tools for intervention in mental illness
RBF-ANN	Radial basic function based artificial neural network
FORCe	Fully online and automated artifact removal for BCI
SFA	Signal fraction analysis
GSVD	Generalized singular value decomposition
EDS	Exponentially damped sinusoidal
RMVB	Robust minimum variance beamforming
STF-TS	Space-time-frequency time/segment
GMDH	Group method of data handling
PNN	Polynomial neural network
DTT	Decision tree technique
ARX	Auto-regressive exogenous
WNN	Wavelet neural network
CSPA	Component subspace projection algorithm
SR	Spectral ratio
FLN-RBFN	Functional link neural network with adaptive radial basis function networks
FLNN-ANFIS	Functional link neural network with adaptive neural fuzzy inference system
MARA	Multiple artifact rejection algorithm
FOOBI	Fourth-order Tensor method
UBSS	Underdetermined blind source separation
TDSEP	Temporal de-correlation source separation
LAMIC	Lagged auto-mutual information clustering
ERP	Event-related potential
CNR	Contrast-to-noise ratio
EEMD	Ensemble empirical mode decomposition
MCCA	Multi-set canonical correlation analysis
WPT	Wavelet packet transform
Local SSA	Local singular spectrum analysis
MSSA	Multivariate singular spectrum analysis
CC	Correlation coefficient
RRMSE	Relative root-mean-squared error
LPM	Linear programming machine
JBSS	Joint blind source separation
PSNR	Peak signal-to-noise ratio
EAWICA	Enhanced automated wavelet-ICA
SSA	Stationary subspace analysis
CBSS	Constrained BSS
MI	Mutual information
FASTER	Fully automated statistical thresholding for EEG artifact rejection
OSET	Open-source electrophysiological toolbox
AAR	Automatic artifact removal
ADJUST	Automatic EEG artifact detector based on the joint use of spatial and temporal features
BCI	Brain-computer-interface

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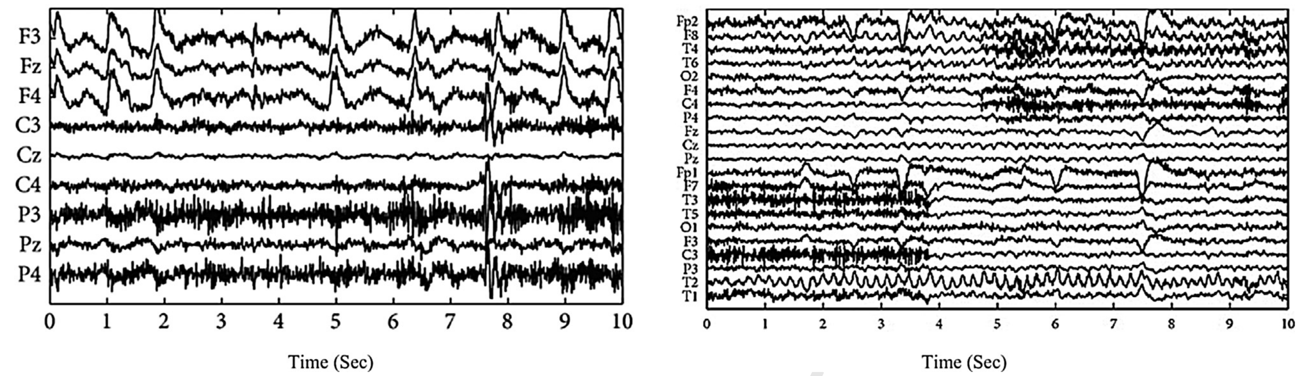

Figure 1 Left: a scalp EEG segment where all channels are more or less contaminated with muscle activity during the 10 seconds. Right: the 10-second scalp EEG recordings with 21 channels from a long-term Epilepsy Monitoring Unit (OSG EEG recorders, Rumst, Belgium). The seizure EEG was contaminated with muscle artifacts and eye blinks. Muscle artifacts can be observed between 0 sec and 3.9 sec on channels F7, T3, T5, C3, and T1 and between 5 sec and 10 sec on channels F8, T4, F4, C4, and P4 [16].

Table 2 EEG rhythms with their corresponding frequency bands.

Rhythm or transient	EEG signal component	Frequency band (Hz)
Rhythm	Delta	< 4
	Theta	4—8
	Alpha	8—13
	Beta	14—30
	Gamma	> 30
	Mu	7.5—12.5
Transient	Seizure and inter-ictal activities	0.5—30

Existing artifact handling methods

In this section, we present the different artifact handling methods found from extensive literature review.

Artifact avoidance

Artifact avoidance is a preventive and precautionary way to avoid or minimize artifacts by instructing the subject to remain still and try to avoid unnecessary blinks, eye/body movements and so on. Also by proper grounding of the EEG recorder, one can reduce the supply mains interference. Although artifact avoidance is not the best way to get rid of artifacts completely, minimizing artifacts can reduce both the data loss and the computational complexity. However, based on applications, sometimes this is a very unrealistic solution; e.g. in an ambulatory EEG monitoring or brain-computer interface (BCI) application. Moreover, there are several limitations to employ such approach since some of the physiological artifacts (e.g. ECG) are involuntary and therefore cannot be avoided. In addition, the subject cannot limit eye blinking or movement for a long period of time, especially if the subject is a child. Therefore, there will always be some artifacts present in the recording and those should be handled in the digital signal processing domain.

Table 3 Different types of artifacts and their origins.

Artifact types and sources						
Physiological/internal				Extra-physiological/external		
Ocular	Cardiac	Muscle	Others	Instrumental	Interference	Movement
Eye blink Eye movement Eye flatter REM sleep	ECG pulse	Chewing Swallowing Clenching Sniffing Talking Scalp contraction	Gloss kinetic Skin Respiration	Electrode Displacement and pop-up Cable movement Poor ground	Electrical Magnetic Sound Optical EM waves	Head movement Body movement Limbs movement Tremor Other movements

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Artifact detection

Identifying artifacts is the first and most important step for handling artifacts. Often the artifacts overlap with EEG signals in both spectral and temporal domains such that it becomes difficult to use simple filtering or straight forward signal processing technique. In many applications, it is required to identify or separate artifacts in real-time, therefore knowing both the artifact and signal characteristics is really necessary in order to detect them faster. Detection of artifacts may refer to detecting a particular epoch or detecting an independent component to be artifactual after performing independent component analysis, ICA (detail about ICA is given later in this section).

Whether it should be detected in time domain or frequency domain or even in both by utilizing time-frequency analysis, this decision depends on the type of artifacts and/or type of applications. Some of other factors for selecting a detection method include:

- availability of a reference artifact source;
- the number of available recording channels;
- the need for removing the artifacts after detection stage.

A few existing methods adopted the idea of machine learning for artifact separation from useful EEG signal by training a classifier with (supervised) or without (unsupervised) labeled training datasets. Once artifactual epochs are identified by applying a machine learning algorithm, such epochs are either highlighted as artifact annotator to the clinicians for helping in decision making (e.g. epileptic seizure detection) or can be rejected before examination from clinician or before sending to automated signal processing system [70].

Machine learning techniques are mainly two types: supervised and unsupervised learning. Among supervised learning algorithms, two most popular methods used for classification between artifact and brain signals are artificial neural network (ANN) [11,38,40,57,83] and support vector machine (SVM) [6,44,70,71,85,87]. Among unsupervised learning, k-means clustering and outlier detection are most common in this particular area of research [70]. A basic approach to classify artifact from EEG by using the machine learning classifier is shown in Fig. 2.

Artifactual segment rejection

One way to reduce the effects of artifacts is to reject/cancel the epoch or segment of EEG data which is labeled as artifactual. The major drawback of this method is that it also removes important EEG information, which results in the loss of data [52,66]. This was an early technique of handling artifacts, but nowadays with the introduction of recent signal processing techniques, the preference is for techniques for artifact removal or correcting them instead of rejecting the data epoch. However, in certain applications, this technique can still work reasonably well, e.g. offline analysis or during training of any classifier.

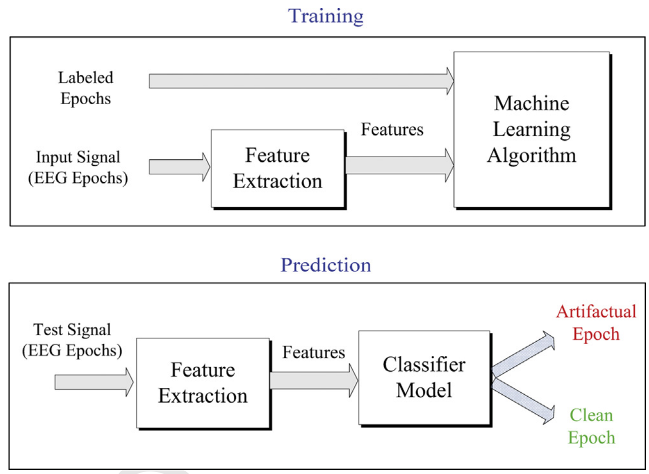

Figure 2 Machine learning classification for identifying artifactual epoch from clean EEG epoch.

Artifact removal

Artifact removal involves canceling or correcting the artifacts without distorting the signal of interest. This is primarily done in two ways: either by filtering and regression or by separating/decomposing the EEG data into other domains.

Regression

Regression analysis [43,101], using a multi-modal linear model between observed and a reference signal, is a traditional way of identifying artifactual samples and consequently removing such sample that do not belong to the model. Observed artifact-contaminated EEG signal and an artifact reference signal are common methods for removing some physiological artifacts such as ocular and cardiac artifacts.

However, such regression analysis often fails when there is no reference channel available. In addition, EEG signal being non-linear and non-stationary process, linear regression is not the best choice for analysis in such applications. Moreover, it can only be used to treat few particular types of artifact, not all types.

Blind source separation

One of the most popular artifact detection/removal methods is based on blind source separation (BSS) [33,43,62,86,97], which aims to extract the individual unknown source signals from their mixtures and possibly to estimate the unknown mixing channels using only the information within the mixtures observed at the output of each channel with no, or very limited, knowledge about the source signals and the mixing channel. Let denote by X the observed signals in multi-channel recordings, which is assumed to be linear mixture of the sources, S with additive white noise vector N, i.e.

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

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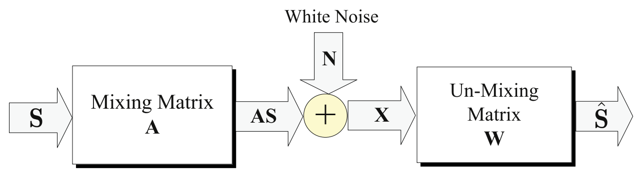

Figure 3 Illustration of blind source separation technique.

Then, the objective is to find an estimate of the linear mixture matrix A, denoted by W by an iterative process and obtain an estimate for the source signals as follows

$$\hat{S} = WX \tag{2}$$

A basic BSS technique is illustrated in Fig. 3. The main assumption with BSS is that the number of sources can be at most (or lower) equal to that of observed channels and the sources need to be independent (for ICA) or maximally uncorrelated (for CCA) from each other:

- ICA: independent component analysis (ICA) is based on blind source separation (BSS) technique where it is assumed that the sources are linearly independent. The major problem with ICA-based artifact detection and removal is that, it is often not automatic. It requires manual intervention to reject independent components (ICs) with visually detected artifacts after decomposition. However, it (i.e. artifact detection and removal) can be made automatic by labeling the ICs through some features that can quantify the possibility of being artifactual. Such procedure is performed by combining ICA with another complementary method such as Wavelet Transform or Empirical Mode Decomposition (EMD) or using classifier like SVM or even with a help of reference channel [110]. However, even in such case, the artifactual ICs may also contain some residual neural signals. Therefore, during signal reconstruction after completely rejecting that particular IC, it introduces distortion to the neural signal. Another problem is that it cannot operate on single-channel data, since the number of recording channels must be at least equal to the number of independent sources. The computational complexity is another factor that limits the choice of ICA for artifact removal in applications that require online/real-time implementation of the algorithm. Finally, the involvement of iterative process in computing ICA algorithm makes it difficult to perform robustly. E.g. ICA may be useful to remove global artifacts such as ocular artifacts [11,27,31,43,46] or sometimes other physiological artifacts. There are few works reported the use of modified [23] or constrained ICA [1,41,79,86] for automated and better performance in artifact detection and removal;
- CCA: canonical correlation analysis or CCA is another BSS method for separating a number of mixed or contaminated signals that uses second-order statistics (SOS) to generate components derived from their uncorrelated nature. By looking for uncorrelated components, the approach uses a weaker condition than statistical independence sought by the ICA algorithm. ICA does not take temporal correlations into account while CCA addresses this point by being capable of finding uncorrelated components [91]. So the spatial correlation being zero while it optimizes only the temporal correlation (i.e. auto-correlation). Then CCA attempts to find an ordered set of components from maximum auto-correlation to least auto-correlation. The component with least auto-correlation corresponds mostly to artifacts. The advantages of CCA over ICA are being automatic and more computationally efficient;
- MCA: morphological component analysis (MCA) decomposes the recorded signal into components that have different morphological characteristics where each component is sparsely represented in an over-complete dictionary [91]. It is only applicable to certain known artifacts whose wave shape or morphology are known and stored in a database. The efficacy of this method greatly depends on the available artifact-template database. In [106,107], MCA is used to remove ocular artifacts and some of the muscle artifacts originating from jaw clenching, swallowing, and eyebrow rising.

Time-frequency representation

Time-frequency analysis of non-stationary time series data is quite popular in biomedical signal processing, e.g. in EEG signal processing. The reason of using simultaneous time and frequency domain analysis is because of the non-stationary properties of this type of signal. Therefore, any momentary change in frequency values for any signal components (e.g. either artifact or seizure) [76,90] can be captured in a particular temporal window. In [69], a time-frequency analysis of ocular artifacts (OAs) including blinks and saccades found in EOG have been reported where the results reveal that frequencies up to 181 Hz can be present in a subject's EOG for certain tasks. This finding suggests that if EOG is used for ocular artifact removal from EEG, then EOG should be sampled at least 362 Hz to avoid aliasing.

The common time-frequency representation is based on the short-time Fourier Transform (STFT). This method is not so effective as it has uniform time-frequency resolution at all frequencies. For EEG, since the bandwidth is around 0.5–120 Hz (although most of the time we are only interested in < 30 Hz) and many of the artifacts (specially motion and ocular artifacts) appear in the lower frequency region (< 10 Hz), therefore, it is required to have high frequency resolution in lower frequency region which STFT cannot provide. To address this issue, a wavelet-based approach can be used as the wavelet transform, and provides proportional resolution in each frequency band suitable for EEG signals.

Wavelet transform

The wavelet transform is a time-scale representation method that decomposes signal $f(t)$ into basis functions of time and scale which are dilated and translated versions of a basis function $\psi(t)$ called mother wavelet [51]. Translation is accomplished by considering all possible integer translations of $\psi(t)$ and dilation is obtained by multiplying t by a scaling factor, which is usually factors of 2. The following equation shows how wavelets are generated from the mother wavelet:

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^{j/2}t - k) \tag{3}$$

where j indicates the resolution level and k is the translation in time. This is called dyadic scaling, since the scaling factor

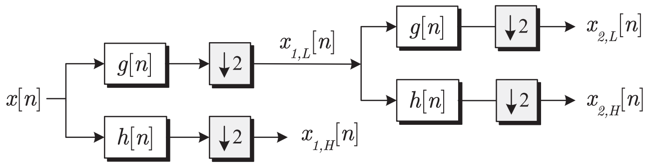

Figure 4 An example structure of 2-level decomposition by discrete wavelet transform.

is taken to be 2. Wavelet decomposition is a linear expansion and it is expressed as

$$f(t) = \sum_{k=-\infty}^{+\infty} [c_k \phi(t-k)] + \sum_{k=-\infty}^{+\infty} \sum_{j=0}^{+\infty} d_{j,k} \psi(2^j t - k) \tag{4}$$

where $\phi(t)$ is the scaling function and c_k and $d_{j,k}$ are the coarse and detail level expansion coefficients, respectively. A wide variety of functions could be chosen as the mother wavelet as long as following equation is satisfied:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{5}$$

There are several techniques based on wavelet theory, such as wavelet packets, wavelet approximation and decomposition, discrete and continuous wavelet transform, and so forth. The most commonly used technique is Discrete Wavelet Transform (DWT). The DWT is derived from continuous wavelet transform with discrete input. The relation between input and output can be represented as

$$x_{a,L}[n] = \sum_{k=1}^{N} x_{a-1,L}[2n-k]g[k] \tag{6}$$

$$x_{a,H}[n] = \sum_{k=1}^{N} x_{a-1,L}[2n-k]h[k] \tag{7}$$

where $g[n]$ is a low pass filter just like scaling function and $h[n]$ is a high pass filter just like mother wavelet function. Briefly, discrete wavelet transform is entering of a signal into a low pass filter to get the low frequency component and into a high pass filter to get the high frequency component. An example structure of 2-level decomposition by discrete wavelet transform is shown in Fig. 4 [51].

Once the signal is decomposed into detail and approximate coefficients, thresholding is applied on the coefficients to denoise the signal from artifacts. Then the new sets of coefficients (all detail with final level approx. coefficients) are added up to reconstruct back the artifact-reduced signal.

Empirical mode decomposition

EMD is an empirical and data-driven method developed to perform on non-stationary, non-linear, stochastic processes and therefore it is ideally suitable for EEG signal analysis and processing. However, the computational complexity of EMD is quite heavy, so may not be suitable for online applications. Moreover, the theory behind EMD is still not complete and so far used in empirical studies, therefore it is difficult to predict its robustness in all EEG recordings.

EMD algorithm decomposes a signal, *s[n]* into a sum of the band-limited components/functions, *c[n]* called intrinsic mode functions (IMF) with well defined instantaneous frequencies [58,94]. 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) any point, the mean value of the two envelopes defined by the local maxima and the local minima has to be zero [58]. The general process flow of EMD algorithm is shown in Table 4. EEMD: it is an enhanced version of EMD (enhanced empirical mode decomposition) and inspired from the fact that EMD algorithm is very sensitive to noise, which often leads to mode mixing complication. Therefore, EEMD is proposed which uses an average number of ensembles (IMFs) from EMD as the optimal IMFs thus it provides a noise-assisted data analysis method [94].

Table 4 Process flow of EMD algorithm to generate IMFS.

Input: data sequence *s[n]*
1. Identify all the local extrema
2. Separately connect all the maxima and minima with natural cubic spline lines to form the upper, *u[n]*, and lower, *l[n]*, envelopes
3. Find the mean of the envelopes as *z[n] = [u[n] + 1[n]]/2*
4. Take the difference between the data and the mean as the proto-IMF, *h[n] = s[n] − z[n]*
5. Check the proto-IMF against the definition of IMF and the stoppage criterion to determine if it is an IMF
6. If the proto-IMF does not satisfy the definition, repeat step 1 to 5 on *h[n]* as many time as needed till it satisfies the definition
7. If the proto-IMF does satisfy the definition, assign the proto-IMF as an IMF component, *c[n]*
8. Repeat the operation step 1 to 7 on the residue, *q[n] = s[n] − c[n]*, as the data
9. The operation ends when the residue contains no more than one extremum

Adaptive filtering

An adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust those parameters according to an optimization algorithm [89]. The filter weights can adapt based on the feedback from output of the system and it requires a reference input to compare the desired output with the observed output. An improved adaptive filtering by optimal projection which is based on common spatial pattern for artifact removal is mentioned in [9,10], especially for epilepsy patient's EEG [74]. Let $s[n]$ denote the observed signal which is combination of the original EEG, $x[n]$ and additive artifact *r[n]*. Then, if the artifact source $v[n]$ is available from a dedicated channel (e.g. EOG or ECG); an adaptive algorithm (e.g. LMS, RLS, etc.) can be used to derive an artifact-free EEG, $x'[n]$ given that the desired EEG and artifact signal are independent (or at least uncorrelated [91]). An illustration of the use of adaptive filter for EOG artifact removal is shown in Fig. 5.

Principal component analysis (PCA)

PCA is a type of spatial filter that transforms the time domain datasets into a different space by rotating axes in

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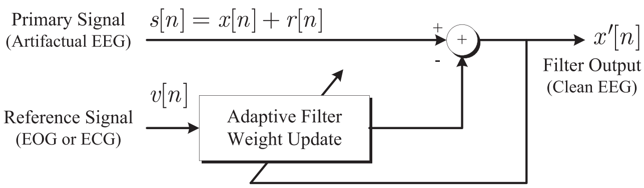

Figure 5 Typical use of adaptive filtering in canceling physiological artifacts with available artifact source channel as reference.

an N-dimensional space (where *n* is the number of variables or EEG channels) such that each dimension in the new space has minimum variance and the axes are orthogonal to each other [17]. PCA reduces data dimension and highlights specific features of data, which is usually difficult to identify in the spatially unfiltered data as the new components are created by weighted combinations of all EEG channels. Two recent papers proposed artifact removal method based on PCA: Turnip [98] reported the use of robust PCA after preprocessing is done based on wavelet de-noising and band-pass-filtering; while Turnip and Junaidi [99] compared PCA with ICA for artifact removal and found ICA performs better than PCA. Both these papers have evaluated their method qualitatively; therefore, it is not possible to comment exclusively on the efficacy of PCA in detecting and removing artifacts. One important limitation of PCA (or SVD) is that it fails to separate/identify ocular or similar artifacts from EEG when amplitudes are comparable since PCA depends on the higher order statistical property [79].

Hybrid methods

In recent years, researchers have been keen to utilize the advantages of different methods by combining them into a single method for artifact detection and removal, i.e. a hybrid method which has two or more stages. Some of these methods are discussed below:

- wavelet-BSS: this hybrid method formed by integrating two popular methods: wavelet transform and blind source separation is mainly inspired from the fact that only BSS-based separation of artifactual components (e.g. ICs) is often erroneous since the separated artifactual component also contains residual neural information. Therefore, completely rejecting such component will introduce significant distortion in reconstructed EEG signal. Hence, the multi-channel datasets are transformed into ICs or CCs and then possible artifactual component is decomposed by wavelet transform to different frequency bands of detail coefficients. After that, the artifactual coefficients are denoised by thresholding, which eventually preserve the residual neural signals of low amplitude after thresholding the higher artifactual segments. The related articles are [14,34,50,52] for wavelet-ICA, [109] for wavelet-CCA. On the other hand, there are similar hybrid methods that can be applied to single-channel EEG data by reversing the order of wavelet transform and BSS blocks. For example Calcagno et al. and Mammone and Morabito [12,52] reported artifact removal by first decomposing signal into wavelet coefficients then artifactual coefficients are passed through BSS block to separate artifacts from neural signal. However, typically the prior way is more known to the research community s wavelet enhanced ICA or wavelet enhanced CCA. An example of such method is shown in Fig. 6. Please note that the type of wavelet transform can be DWT, CWT, SWT or sometimes WPT [8];
- EMD-BSS: this hybrid method involves BSS with EMD instead of wavelet transform. The difference is that usually the first stage is to decompose the signal into IMFs by EMD or EEMD and then apply BSS (ICA or CCA) on the IMFs to identify artifactual component followed by rejecting the artifactual IC or CC. The general process flow of this hybrid method is also shown in the same Fig. 6. Such methods are reported in [16,94,108];
- BSS-SVM: Shoker et al. [87] reported a hybrid BSS-SVM algorithm for eye blink and ECG artifact removal where certain carefully chosen features are extracted from separated source components and then fed into a SVM classifier to identify artifact components followed by removing them. Finally, the rest of the source components are re-projected to reconstruct artifact-free EEG. The whole system is illustrated in Fig. 7;
- REG-BSS: Klados et al. [43] reported a hybrid methodology by combining BSS and regression-based adaptive filtering (with vEOG and hEOG as reference channels) for rejection

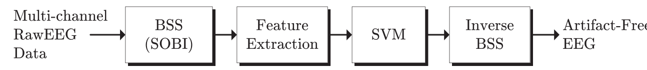

Figure 7 Process flow of the hybrid BSS-SVM algorithm.

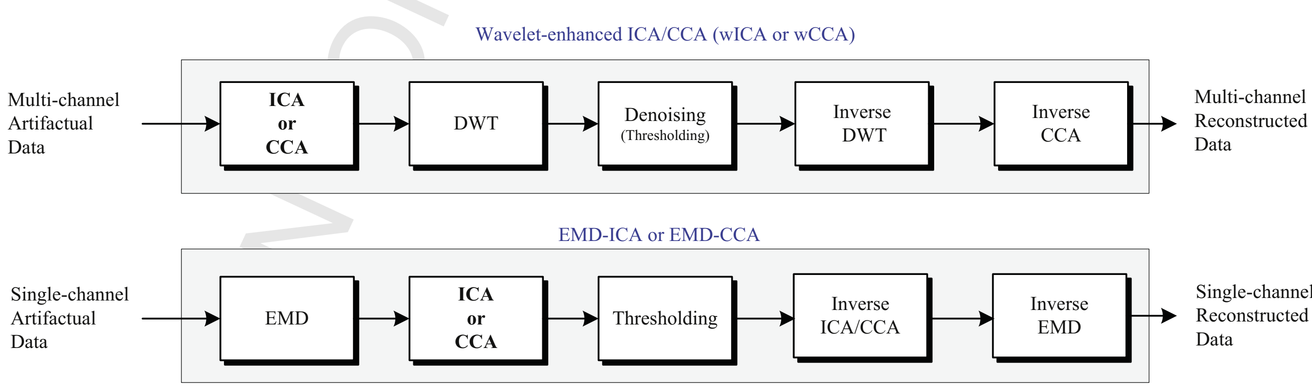

Figure 6 General process flow of EMD-BSS and wavelet-BSS methods.

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Figure 8 Process flow of the hybrid REG-BSS methodology.

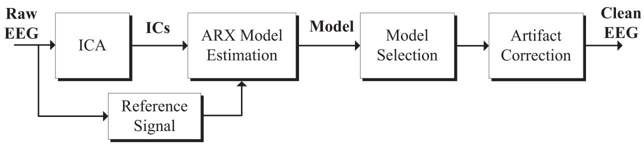

Figure 9 Process flow of the hybrid ICA-ARX methodology.

of ocular artifacts as shown in Fig. 8. Similar techniques have been used by [31] to remove ocular artifacts by combining ICA and adaptive filtering. Another hybrid approach combining ICA and Auto-Regressive eXogenous (ARX) was proposed by Wang et al. [102] to remove ocular artifacts robustly as shown in Fig. 9. In this method, ARX is used to reduce the negative effect induced by ICA by building the ARX multi-models based on the ICA correlated signals and the reference EEG that are selected prior to the artifact-contamination;

- other hybrid methods: Nguyen et al. [63] report EOG artifact removal using a hybrid method combined of Wavelet decomposition and Artificial Neural Network and termed as Wavelet Neural Network (WNN) where the reference EOG channel is only required during training of ANN classifier. A method combining DWT and ANC (Adaptive noise canceler) is proposed in [73] to remove ocular artifacts where the OA reference is derived from DWT decomposition and then used in the adaptive filter as reference. On the other hand, Navarro et al. [60] used the combination of EMD and adaptive filter (with RLS algorithm) to remove ECG artifacts from EEG recordings. The authors in [38] presented a new way to remove EOG and EMG artifacts from EEG by using a hybrid combination of functional link neural network (FLNN) and adaptive neural fuzzy inference system (ANFIS). The ANFIS usually has two parts: a non-linear antecedent and a linear consequent; however, in their proposed system, the second part is replaced with the FLNN to enhance the non-linear approximation ability. Then an adaptive filtering algorithm adjusts the parameters of both ANFIS and FLNN.

Statistical features

Several statistical features [37,57,66] are used in machine learning classifier or during threshold calculation in wavelet/EMD/ICA-based methods for separating or identifying artifacts from EEG signal of interest. Some of such features are discussed in Appendix A.

Comparison between methods

In order to compare different artifact handling methods qualitatively, several factors need to be considered that can evaluate the pros and cons of these methods. Such factors are described as follows: a detailed comparison between the existing artifact detection and removal methods in the literature found from recognized journals is provided in Table 5.

Removal performance

The performance evaluation of artifact removal methods found in the literature is always problematic. It can be done either by visually by expert(s) which is subjective (not standard) or by synthetic/semi-synthetic data (but uncertainty of reconstructed data whether perfectly realistic or not). Since there is neither any ground truth data available nor any universal or standard quantitative metric(s) used in the literature that can capture both amount of artifact removal and distortion. Therefore, it is quite difficult to compare different artifact removal methods based on their ability to remove artifacts since very few quantitative evaluations have been reported in the literature. Most of the published articles evaluated their method in terms of some qualitative plots. In addition, very few of them quantified the distortion to desired EEG signals due to the removal effect. Therefore, it is not fair to tell which performs best based on the study.

Automatic or semi-automatic

Most of the EEG-based applications require automated information processing, particularly when it is an online/real-time implementation. In addition, manual identification of artifactual component or epoch is very time-consuming and laborious for multi-channel long-term data sequences. Therefore, many signal processing techniques have been proposed, and some useful a priori signal or artifact statistics/characteristics have been utilized. Among them, BSS-based techniques can sometimes be semi-automated because of identification of artifactual component may require some training or parameter selection/tuning. Although there are few papers available that propose automated identification of ICs after ICA [104,111]; however, they both require training samples for supervised classification and in addition requires an extra information in the form of contact impedance measurement [31]. If the method involves ICA for automatic detection of artifacts, then there has to be another stage (or method) in order to make the whole process automated.

Real-time/online implementation

Online/real-time implementation requires the algorithm to be fast enough and to have low-enough complexity for such application. Here, online implementation refers to the algorithms implemented in software platform capable of online/real-time processing, not in hardware platform. However, some EEG-based applications such as wireless ambulatory EEG monitoring may require on-chip implementation of the artifact detection/removal algorithm. In such cases, the computational complexity has to be minimal, which is a great challenge, and so far to the best of our

Q10 **Table 5** Comparative analysis of artifact removal methods found in literature published in recognized journals.

Articles	Type of artifacts	Method	Online/ real-time	Automated	Reference	Multi/ single-channel	Application
Shoker et al. [87]	Eye blink	ECG BSS-SVM (SOBI-SVM)	NIA	Y	N	Multi	General; e.g. ERP analysis
Park et al. [72]	ECG	EIH-EAS	Y	Y	N	Single	General; e.g. sleep/wake state or epilepsy monitoring
Hamaneh et al. [34]	EKG	ICA-CWT	N/A	Y	Template	Multi	General; e.g. epilepsy monitoring
Shao et al. [85]	Eye blink + ECG	ICA-weighted PWC-PSVM	N/A	Y	Template	Multi	General
Zhao et al. [110]	Ocular	DWT-APF	Y	Y	N	Single	Monitor mental health (OPTIMI), portable applications
De Clercq et al. [20]	Muscle	CCA	N	N	N	Multi	Epilepsy monitoring; applied on ictal datasets
Ng et al. [62]	EOG + EMG	SOBI-SWT	N/A	Y	N	Multi	μ rhythm extraction
Mateo et al. [54]	Ocular	RBF based ANN	N/A	Y	EOG channel (vEOG + hEOG)	Single	General
Anderson et al. [4]	EOG + 60-Hz noise	GSVD-SFA	May be	N	EOG channel	Multi	BCI; mental task
Van Huffel et al. [19]	Muscle + 50-Hz noise	SVD	N/A	N	N	Single/multi	Ictal EEG
Daly et al. [18]	Head movement	ICA	N	Semi-automated	Accelerometer	Multi	General; BCI
Noureddin et al. [68]	EOG + Blink	Adaptive Filter (RLS and H_α)	Y	Y	Eye Tracker	Multi	General
Peng et al. [73]	Ocular	DWT-ANC	May be	Y	N	Single	OPTIMI, portable applications
Nazarpour et al. [61]	Blink	STF-TS-RMVB	Y	Y	N	Multi	General
James et al. [41]	Ocular	cICA	Y	Y	Derived reference	Multi	Seizure analysis
Schetinin et al. [83]	ECG, EOG, muscle, and electrode noise	PNN-GMDH-DTT	N/A	Y	Template	Multi	Sleeping newborns
Mahajan et al. [50]	Eye blink	ICA-DWT with statistics	N/A	Y	N	Multi	General
Kierkels et al. [42]	EOG	Kalman filter	N/A	Y	Eye tracker	Single	General
Sweeney et al. [94]	Motion	EEMD-CCA	N/A	Y	N	Single	Ambulatory single-channel applications
Wang et al. [102]	Ocular	ICA-ARX	N/A	Y	N	Multi	General
Burger et al. [11]	EOG	ICA-WNN	N/A	N	N	Multi	General

Table 5 (*Continued*)

Articles	Type of artifacts	Method	Online/ real-time	Automated	Reference	Multi/ single-channel	Application
Klados et al. [43]	Ocular	REG-ICA	N	N	EOG	Multi	General
O'Regan et al. [71]	Head movement	Feature fusion (69) to SVM	N/A	Y	Gyroscope	Single	Ambulatory EEG: seizure monitoring + BCI
Ma et al. [49]	Ocular	BSS-based CSPA	N/A	Y	N	Multi	General
Ma et al. [48]	Muscle	ICA-SR	N/A	Y	N	Multi	General
Jafarifarmand et al. [40]	Ocular muscular and ECG	Adaptive FLN-RBFN-based filter (ANC)	N/A	Y	ECG, EOG, EMG	Single/multi	General
Nguyen et al. [63]	EOG	WNN	Y	Y, training required	EOG only for training	Single	Mental and visual task
Hu et al. [38]	EOG and EMG	FLNN-ANFIS	May be	Y	EOG, EMG	Single/multi	General
Hartmann et al. [35]	Most types	Iterative Bayesian Estimation (MMSE)	N/A	Y	N	Single/multi	Epilepsy monitoring
Sameni et al. [81]	Ocular	Generalized Eigenvalue decomposition	N/A	Y	EOG	Multi	General
Akhtar et al. [1]	Most types	Spatially cICA + Wavelet de-noising	N/A	Y	May be sometimes	Multi	General
Molla et al. [58]	EOG	Adaptive filtering (EMD-based filter)	N/A	Y	Fractional Gaussian noise	Single	General
LeVan et al. [45]	Ocular, EMG, movement	ICA + Bayesian classification	N/A	Y	ECG	Multi	Ictal scalp EEG for epilepsy diagnosis
Lawhern et al. [44]	Ocular, muscle, movement	AR model (feature) + SVM	Yes	Y	N	Single	Real-time EEG applications
Hallez et al. [33]	Muscle and ocular	BSS (CCA/spatial cICA) + RAP-MUSIC	N/A	Semi-automated*	N	Multi	Ictal EEG source imaging
Bhattacharyya et al. [6]	All of them	26D features + bi-classification	N/A	Y	N	Single	Neonatal seizure detection
Flexer et al. [27]	Ocular	ICA	N/A	Semi-automated	N	Multi	Blind subjects
Teixeira et al. [96]	EOG + baseline drifts	Local SSA + embedding dimension	N/A	Y	N	Single	General
Ge et al. [28]	Ocular	FOOBI based on UBSS	N/A	Y	N	Multi	Only for healthy subjects; not for epilepsy

Table 5 (*Continued*)

Articles	Type of artifacts	Method	Online/ real-time	Automated	Reference	Multi/ single-channel	Application
Nicolaou et al. [64]	EOG, EMG and ECG	TDSEP + LAMIC	N/A	Y	EOG	Multi	Discovery and analysis of ERP
Rashed-Al-Mahfuz et al. [77]	Ocular	EMD	N/A	Y	Simulated	Multi	BCI
Guerrero-Mosquera et al. [31]	Ocular	Adaptive filtering + ICA	N/A	Y	Fpl, Fp2, F7 and F8 Electrodes	Multi	General
Mammone et al. [52]	Ocular + muscle + electrical shift	EAWICA (wICA)	N	Y	N	Multi	General
Winkler et al. [104]	EOG + EMG	TDSEP (based on ICA) + LPM	Y	Y	N	Multi	BCI
Chen et al. [16]	Muscle	EEMD-JBSS	N/A	Y	N	Single	General + ictal EEG
Zeng et al. [108]	EOG	SSA (BSS) + EMD	N	N	N	Multi	Diagnosis

knowledge, no real-time hardware implementation has been performed.

Single or multi-channel

BSS-based methods require multi-channels to function, the more number of channels the better for separating individual sources. Therefore, such methods cannot be used in low-channel (e.g. 4—6) or single-channel based applications (e.g. in ambulatory monitoring of epilepsy patient or ambulatory BCI-prosthesis). On the other hand, Wavelet transform and EMD-based techniques can work with single-channel analysis by decomposing a single data sequence into multiple components (approx./detail coefficient for wavelet decomposition and IMF for EMD).

Reference channel

Most of the available methods require a dedicated artifact channel to be functional. In order to remove ocular or cardiac artifacts, the reference channel often provides satisfactory complementary information to identify ECG/EOG artifacts. Besides, real-time contact impedance measurement can provide the complementary information about artifacts due to electrode pop, movement or loose connection. Some movement tracking devices such as motion captured camera, accelerometer and/or gyroscope can help to detect motion artifacts.

EOG

Many articles reported to remove EOG artifacts by the use of EOG reference channel [27,43,110]. In [110], a hybrid denoising method has been reported that combines discrete wavelet transformation (DWT) and an adaptive predictor filter (APF) for automatic identification and removal of ocular artifacts for portable EEG applications which is found to achieve lower MSE and higher correlation between cleaned and original EEG in comparison with existing methods such as wavelet packet transform (WPT) and independent component analysis (ICA), discrete wavelet transform (DWT) and adaptive noise cancellation (ANC). Another article [43] reported an automated ocular artifact removal method using adaptive filtering and ICA with the help of vertical (vEOG) and horizontal (hEOG) EOG channel as reference. On the other hand, Flexer et al. [27] proposed an ICA-based ocular artifact removal method from blind subjects' EEG utilizing both vertical and horizontal EOG references.

ECG

Authors in [21] proposed removal/reduction of ECG/cardiac artifacts from EEG using a separate ECG reference channel. In [31], an automatic method based on a modified ICA algorithm has been proposed that works for a single-channel EEG and the ECG (as reference) which gives promising results when compared with two popular methods that use a reference channel namely ensemble average subtraction (EAS) and adaptive filtering. The other two articles proposed their methods for application in neonatal EEG monitoring. Another paper [60] proposed a combination of EMD and adaptive filtering based method for ECG artifact removal in preterm EEG and reported up to 17% improvement in correlation coefficient between original and cleaned datasets compared with removal by only adaptive filtering.

Eye tracker

Both Kierkels et al. [42] and Noureddin et al. [68] reported techniques for removal of ocular artifacts by using an eye tracker as reference. The advantage of using eye tracker is that it can reduce the undesired EEG distortion produced by using an EOG channel as reference since EOG not only captures ocular events but also some frontal EEG events. Besides, in practical daily applications, the use of eye tracker removes the requirement of EOG electrodes attached to the face. Results in [42] show significantly improved performance in removing of only eye movement artifacts by combining Kalman filter with the eye tracker information compared with three other popular methods namely Regression, PCA, and SOBI. On the other hand, Noureddin et al. [68] introduced an online algorithm for ocular artifacts (both movements and blink) removal from EEG by utilizing a high-speed eye tracker (> 400 Hz) along with the frontal EEG as reference instead of EOG channel. The article used two adaptive filters (RLS and H) to prove the efficacy of their proposed technique, which was shown to outperform the techniques using only EOG as reference.

Accelerometer

There are few articles reported to have used accelerometer recordings in conjunction with EEG recordings for detecting motion artifacts [82,93]. In [82], it has been shown that movement artifacts can be detected automatically using an accelerometer with a developed algorithm based on AR modeling and thus can increase the speed efficiency for automatic computation of EEG model parameters compared with manual detection of movement artifacts. Sweeney reported in [93] that the use of accelerometer as reference channel not only can detect motion artifacts but also can remove them with the use of different filtering techniques such as adaptive filters, Kalman filtering and Wiener filtering.

Gyroscope

Authors in [71] proposed to detect different head movement artifacts automatically by using a gyroscope as complementary features in fusion with EEG features and finally with the help of SVM, to classify artifacts from neural information. The method is inspired by the realization of an artifact detection system for implementing with the point-of-care REACT (Real-time EEG Analysis for event detection) technology that has potential application in the detection of neurological events (e.g. seizure events) in adults. The artifacts were generated for 10 different types of head-related movements using 14-channel Emotiv EEG headset and the movement time was recorded for validation during artifact detection. The reported accuracy in terms of Avg. ROC areas was 0.802 and 0.907 for participant independent and dependent systems respectively.

Contact impedance measurement

Bertrand et al. and Mihajlovic et al. [5,55,56] reported that by measuring the change in contact impedance due to head movements can help to estimate the motion artifacts and by utilizing this information with an adaptive filter in combination with band-pass filtering, the artifacts can be reduced significantly in real-time. The article also studies the effect of head movement artifacts on EEG recordings results in contaminating the spectral domain in < 20 Hz frequency.

Motion captured camera

Authors in [32] proposed a channel and IC-based method to remove movement artifacts during walking and running from a high-density EEG recordings (248-channel) with the help of kinematics and kinetics information acquired from a 8-camera, 120 frames/s, motion capture system. The subject was asked to walk and run on a custom built, dual-belt, force measuring treadmill with two 24-inwide belts mounted flush with the floor while simultaneously both brain and body dynamics were recorded. The findings conclude that high-density EEG is possible to use in order to study brain dynamics during whole body movements; and the artifact from rhythmic gait events can be reduced by template regression procedure.

Robustness

Robustness is an important issue in developing any artifact removal algorithm as artifacts are of diverse types and contaminate the EEG differently in different recording environments. Some of the factors that should be considered for robustness include artifact-SNR, type of artifact, duration of artifacts, subject-variability, environmental variability, application-specificity.

Discussion

Current status

Although significant amount of efforts has been made to develop methods for artifact detection and removal in EEG applications, it is still an active area of research. Most of them handle single type of artifact, many of them cannot work for single-channel EEG, some of them require training data, some require a dedicated reference channel, some are designed for general purpose applications that often leads to overcorrection of data and some of them are not fully automated. Some of the currently available major software plug-in GUIs are discussed in Appendix B.

Future direction

Here we present the future direction for handling artifacts by raising realistic issues, proposing some ideas and providing recommendation based on review of existing solutions.

Probability mapping

From the above literature review of existing solutions for artifact handling, it is obvious that artifacts are of different types and not all types will play major role in all EEG-based applications. Sometimes, clinicians prefer manual event detection than automated algorithm for certain disease diagnosis (e.g. seizure detection). However, such manual analysis is also time-consuming. In such cases, if we can give the users an option to choose which particular artifacts they want to be detected and/or removed with what amount (%) for each epoch or data-segment of duration 1-sec (depends on application), then the process would still be automated with tuning facilities for the users either to turn-ON or remain OFF if not required. In order to implement such facility, a probability mapping of artifacts can be proposed (something similar to the idea of [105]) for each epoch of data based on some statistical features to quantify the probability of an epoch to be artifactual. Then the user can opt for some threshold of probability above which he/she may want to remove artifacts while below the threshold, to preserve the epoch as it is. Thus it is possible to design automated artifact detection and removal algorithm, which is application-specific with tuning facility for user. This would greatly enhance the signal analysis process by avoiding the chance of removing important signal information. In addition, it will reduce the unnecessary computational resources and time by focusing on the desired artifacts for detection/removal (i.e. only those types to be expected to affect the signal quality) and ignoring the rest of them.

Standard performance evaluation

One of the important issues in evaluating the performance of any artifact detection or removal method is that there is no universal standard quantitative metric for the researchers to use. Most of the methods mentioned in the literature use some qualitative time/frequency domain plot to evaluate the artifact removal performance or evaluated by the clinical expert. Sweeney et al. [92] proposed a recording methodology for accurate evaluation and comparison between different artifact removal techniques/algorithms which presented the EEG recordings of two separate but highly-correlated channels that allow recording both artifact-contaminated and artifact-free signal simultaneously. It also presented a tagging algorithm employing two accelerometers for generating a quality-of-signal (QOS) metric, which can be used to for multiple purposes such as classification of motion artifacts, activation of artifact removal technique only when required and identification of the artifact-contaminated epochs. Thus, this approach can provide accurate measurements of quantitative metrics for fair performance evaluation.

However, such methodology still requires intervention to the recording technique and also extra reference channel for accelerometer data, which may not be feasible in every application (e.g. portable EEG recordings). Although it is highly encouraged for the removal performance to be evaluated by the domain experts, however, such evaluation varies from one expert to another and still is manual and/or qualitative evaluation. Therefore, it is an urge to have a single standard evaluation method consists of both qualitative and more importantly quantitative metrics or ways for evaluating the performance in a more realistic and fair manner.

Ground truth data

Another reason of not being able to evaluate artifact removal performance fairly is that the lack of availability of ground truth data. It's now equally important to have a public database with sufficiently long-term EEG recordings without or minimal artifacts to be used as a ground truth data. Besides such, an acceptable mathematical model to generate basic EEG rhythms and finally integrate them to simulate an EEG sequence with standard 10—20 system EEG channels is required for quantitative evaluation of any existing/future artifact removal methods. In addition, more study is necessary to characterize as much as possible of all artifact types, specially the motion artifacts for different movement in an ambulatory environment [15]. Thus, it will be easier to label both ground truth EEG and artifacts.

Recommendation

In order to choose the right artifact handling method, we need to consider the particular application, required specification to be satisfied given the computational resources and recording environment available. There are EEG applications where only one or two types of artifacts affect the later stage information decoding or processing, thus it is not wise to attempt to identify and remove all the artifacts as other artifacts may not (or minimally) harm a particular signal processing purpose. If any reference channel is available in the targeted application, then regression or adaptive filtering technique may be a preferred solution. In the case of ambulatory EEG monitoring, when number of channels are fewer, no reference channel is available and wireless EEG transfer preferred, in such case it is recommended to use computationally cheaper method that can work without reference and on single or few channels, e.g. wavelet-based methods since BSS-based methods may not perform satisfactory with less number of channels. In some applications, if it is possible to have some a priori knowledge about artifacts and some training data available, and the application only require to identify artifacts not to remove them, then machine learning based classifiers can be good choice. If the EEG recording involves high-density channels, then PCA may be preferred to reduce the dimensionality before applying any artifact removal methods, such as BSS-based methods. If the application is based on offline analysis, then we can afford some computational expensive techniques such as ICA or EMD.

Conclusions

An extensive analysis of the existing methods for artifact detection and removal has been presented with their comparison, advantages and limitations. The research on handling artifacts present in the typical EEG recordings is still an active area of research and none of the existing methods can be considered as the perfect solution. Most of the solutions do not consider the particular application, therefore, not optimized for that application. Although, most of the removal algorithms provide good performance, however, they are only suitable for offline analysis because of their high computational complexity and unsupervised nature. Some of them even require a dedicated reference channel, which is not feasible for some applications. Further studies are required to characterize the properties of commonly encountered artifacts and to observe the effects of their contamination to the desired later stage signal processing/analysis. Some applications may only require to identify artifacts and not to remove them, e.g. in applications where classification/identification of two classes are required. In such cases, a more realistic mathematical model of the desired event(s) to be identified is essential in order to easily ignore other non-brain signals (i.e. artifacts or interferences). Finally, the future direction will be to provide application-specific solutions with reasonable complexity, optimized performance and most importantly with feasible solutions.

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Disclosure of interest

The authors declare that they have no competing interest.

Uncited Reference Q3

[67].

Acknowledgments

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Appendix A. Statistical features

Time Domain Features

Entropy, *H*: is a measure of uncertainty of information content [78], of a discrete random variable x with possible values $x_1, \ldots, x_n$, can be calculated as:

$$H(x) = E[-\ln(P(x))] \quad (8)$$

Here *E* is the expected value operator and *P(x)* is the probability mass function of *x*.

Kurtosis, *Kr*: Kurtosis is the measure of ''peakedness'' of probability distribution function [50] and is calculated for a real-valued random variable *x* as follows

$$Kr[x] = \frac{\mu^4}{\sigma^4} \quad (9)$$

where μ and σ are the mean and standard deviation of random variable *x*.

Line Length, $\mathcal{L}[n]$: Line length, a signal feature for seizure onset detection as reported by [24,59], for a discrete time signal *x[k]* can be represented by,

$$\mathcal{L}[n] = \sum_{k=n-N}^{n} abs[x[k-1] - x[k]] \quad (10)$$

where *N* is the time window length. Here *N* = *1* sec.

Maximum, *M*: It is the maximum or peak value of an epoch and noted down as a feature.

NEO, Ψ: The ability of Non-linear Energy Operator (NEO) to enhance signal's transition or large amplitude event [53,57,75] is sometimes considered as feature for seizure classification. The NEO operator Ψ applied to a discrete time variable $x[n]$ is calculated as follows

$$\Psi[x[n]] = x[n]^2 - x[n+1]x[n-1] \quad (11)$$

Usually the mean and/or variance of $\Psi[x[n]]$ for each epoch are used as feature(s).

Frequency Domain Features

Spectral features along with temporal or spatial features are often used for EEG classification. As mentioned before, EEG rhythms have different spectral bands, therefore sometimes the relative power in those bands are used as features for classifier training. It is important to note that apart from the rhythms, there are recently reported High Frequency Oscillations (HFO having band of 80–200 Hz), Ripple (200–600 Hz) bands present in EEG. In addition, the frequency band of typical Scalp EEG is 0.05–128 Hz while epileptic seizure appears in 0.5–29 Hz [26]. These bands and their FFT or spectral power are useful features for separating artifacts from EEG.

FFT, *F*: Fast Fourier Transform or FFT is the frequency representation of time domain signal values. For feature extraction, we have used the mean of the absolute of FFT values for each epoch computed over the entire frequency range of EEG signal (i.e. 0–128 Hz).

$$F = mean(abs[FFT(k)]) \quad (12)$$

Maximum FFT, F_{max}: This feature is the maximum or peak value of the absolute of FFT values.

$$F_{\max} = \max(abs[FFT(k)]) \quad (13)$$

Spatial Features

Spatial distribution or topographic mapping helps to identify the origin of many artifacts (e.g. ocular artifacts are dominant in frontal EEG channels) [93]. In addition, some artifacts may appear in several nearby channels (global artifacts such as eye blink) where some appear only in one channel (i.e. local artifacts). Therefore, spatial features along with their spectral content are important to identify artifacts from EEG signals [57,88].

Appendix B. Software plug-ins

FORCe

Fully Online and automated artifact Removal for brain-Computer interfacing or FORCe is the most recent method reported in [18] that is based on a unique combination of WT, ICA and thresholding. Compared with two other state-of-the-art methods namely LAMIC and FASTER, FORCe has been shown to outperform them significantly and is capable of removing different types of artifacts including eye blink, EOG and EMG. One of salient features of FORCe is that it doesn't require any reference channel and can operate on fewer numbers of channels which makes it suitable for ambulatory EEG applications.

FASTER

FASTER stands for *Fully Automated Statistical Thresholding for EEG artifact Rejection* which is an unsupervised algorithm for parameter estimation in both EEG time series and in the ICs of EEG [66]. The achieved sensitivity and specificity is > 90% for detection of EOG and EMG artifacts, linear trends and white noise in the contaminated channels.

LAMIC

Lagged auto-mutual information clustering (LAMIC) is a clustering algorithm developed for automatic artifact removal from EEG [64]. The method involves data decomposition by a BSS algorithm called TDSEP (Temporal De-correlation source SEParation), which is a temporal extension of ICA. Then the components are clustered using the similarity of their lagged Auto-Mutual Information (AMI). This is inspired from the fact that EEG and artifacts are different from their temporal dynamics point of view. The clustering procedure follows the usual steps of hierarchical clustering.

PureEEG

This is an automatic EEG artifact removal algorithm for epilepsy monitoring that based on a neurophysiological model by utilizing an iterative Bayesian estimation scheme [35]. The method targets to remove most of the artifact types and does not require any manual intervention. The authors reported the performance of PureEEG from two independent clinical experts perspective and its found to be significantly improving the readability of EEG recordings after artifact removal.

OSET

OSET is an Open-Source Electrophysiological Toolbox for biomedical signal generation, modeling, processing, and filtering [80]. It can remove cardiac artifacts from any bioelectrical signal including EEG. It can also handle and remove EOG artifacts from multi-channel EEG using techniques based on semi-blind source separation.

MARA

Multiple Artifact Rejection Algorithm (MARA) is an open-source MATLAB-based EEGLAB[2] plug-in which automatically identify the artifact-contaminated independent components for artifact rejection [103,104]. The main part of MARA is a supervised machine learning algorithm that learns from labeled components by experts and utilizes six features based on spatial, spectral and temporal domain. It can handle any type of artifact.

AAR

Automatic Artifact Removal (AAR), a MATLAB toolbox which can be integrated as a plug-in into EEGLAB, includes different artifact removal methods for removing only EOG and EMG artifacts [29]. In order to remove only EOG artifacts, regression-based methods such as least mean squares (LMS), conventional re-cursive least squares (CRLS), stable re-cursive least squares (SRLS) and algorithms based on the H norm are used. For removing both EOG and EMG artifacts, spatial filters based techniques have been adopted.

[2] EEGLAB is an open-source MATLAB-based interactive GUI toolbox for analyzing and processing continuous and event-related EEG, MEG and other electrophysiological signals. It uses ICA, time-frequency analysis, artifact rejection, event-related statistics and different modes for visualizing the averaged or single-trial EEG data [22].

ADJUST

ADJUST, reported by Mognon et al. [57], is an EEGLab supported plug-in for automated EEG artifact detection. This algorithm is based on the combined use of stereotyped artifact-specific spatial and temporal features to automatically identify the artifactual ICs after ICA is performed. Four different artifact types (i.e. eye blink, vertical eye movement, horizontal eye movement and generic discontinuities) are chosen for extracting features such as temporal kurtosis, spatial average and variance difference, maximum epoch variance, spatial eye difference. The key feature of ADJUST is that it is entirely automated and unsupervised with reported accuracy of 95.2% in classifying all of the four artifacts. It can also successfully reconstruct the clean ERP topographies from heavy artifact-contamination.

PREP Pipeline

The PREP pipeline is a standardized preprocessing tool for large-scale EEG analysis [7], which includes an automatically generated report for each dataset processed. The salient features of this toolbox include (i) removal of line-noise without incorporating typical filtering technique, (ii) referencing the signal robustly, and (iii) identification of bad channels relative to the reference.

Makoto's Preprocessing Pipeline

This pipeline is Makoto Miyaksohi's personally recommended EEG preprocess pipeline [30], which is a forever beta version. Interested readers are requested to consult the following link for more details: [http://sccn.ucsd. Q6
edu/wiki/Makoto's preprocessing pipeline].

FieldTrip

This is an open-source MATLAB toolbox for MEG and EEG analysis which offers advanced analysis methods of MEG, EEG, and invasive electrophysiological data, such as time-frequency analysis, source reconstruction using dipoles, distributed sources and beamformers and non-parametric statistical testing [69].

ERPLAB

ERPLAB is also EEGLAB-compatible open-source toolbox for analyzing ERP data, which has artifact rejection capability in both manual and automated manner [47].

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