Recent Study of Artifact Elimination in EEG Signals

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Abstract. The progress of electroencephalography (EEG) has promoted this technology to be widely used in various fields such as computer science, medical engineering, and signal processing because of its non-invasiveness and low cost. However, the quality of EEG recordings may be degraded due to the introduction of artifacts, which has a non-negligible negative impact on subsequent operations. Artifacts are unwanted signals that vary in their source, such as muscular, ocular, and cardiac ones. Many studies have proposed methods to remove artifacts from EEG signals, from the classic ones including filtering, empirical mode decomposition, and blind source separation to the recent frequent introduction of neural networks. This work reviews the highly influential publications in the past 5 years to update the latest headways. Based on the survey of essays and papers, we notice hybrid methods with the greatest proportion. Besides, not only do we discover the development and advancement of the typical methods of signal processing mentioned, but we also find that machine learning techniques are becoming more prevailing and effective for artifact removal. Moreover, we observe that recent works have proposed integrated architectures and blockchain solutions to address the problem globally, regardless of the type of artifact.

Keywords: EEG; Artifacts Removal; Blind source separation; Machine learning; Empirical Mode Decomposition.

1. Introduction

Electroencephalography (EEG) has become one of the most prevailing techniques in brain and neuro-related studies. To record brain activity, it is usually required to place electrodes on the surface of the scalp so that researchers can obtain data from an integrated part of quantities of neurons. Due to its noninvasiveness compared with electrocorticography (ECoG), as well as its convenience and cheapness compared with magnetic resonance imaging (MRI), EEG has been introduced in enormous quantities of facilities.

However, the usage of EEG has to overcome the low quality of signals, since it doesn't use electrodes that are directly in contact with the neurons inside the head. Studies are required to examine and best of all, to remove the interference and noise that degrades the samples. One of the main factors of degradation is the artifacts. Usually, artifacts are mainly considered into two main categories, internal (physiological) and external (non-physiological), based on whether the source is inside or outside the body [1]. The former includes physical motion from as significant as talking or walking, to as tiny as the blink of an eye. The latter are contained with interference from the outside such as micro-displacement of the electrode and the powerline effects. All of these will contaminate the raw signals acquired, resulting in unsatisfied outputs despite the complexity and validity of the subsequent processing.

As important as the issue is, scientists and engineers are dedicated to analyzing, and modeling, with the desire to eliminate the various artifacts without loss of the information. Some achievements provide solutions specific to certain types of artifacts, while others are designed to remove them on a global scale. This work targets recent studies and essays, to summarize the latest products of existing methodologies, motivating the consciousness of possible tools that make further progress, and assisting newcomers in the field to comprehend the full picture in a short period.

The following content goes as follows, Section 2 will present an overall distribution of different methods. Section 3 will demonstrate a detailed explanation of each part. Section 4 will give the conclusion.

2. Overview

To review recent studies in artifacts, this work searches accessible full-text essays including IEEE and Frontiers journals in recent 5 years based on keywords of "EEG", "artifacts removal", and "artifacts elimination" using Semantic Scholar as the search engine. Based on the influence and relevance to the topic, this work selects the top 40 influential essays based on the citations, especially the high-influential ones.

For a global overview, we first examine the measures taken or proposed in each article, extract their main thought, and then divide them into seven categories. Each category represents the root of the idea which each essay applies or is modified from, except for the "hybrid" meaning the article introduces no less than two fundamental methods. The pie chart as illustrated in Fig.1 shows the percentages applied for artifacts removal during the past 5 years. Almost half of the total essays integrate multiple approaches for artifact elimination, while time and frequency domain methods share with similar percentage with that based on machine learning (ML). Essays focus on blind source separation, including principal components analysis (PCA) [2] and independent components analysis (ICA) [3], etc., rank fourth, and the rest of the sort the least, including simple filtering and from empirical mode decomposition (EMD). The following sections will briefly introduce each category.

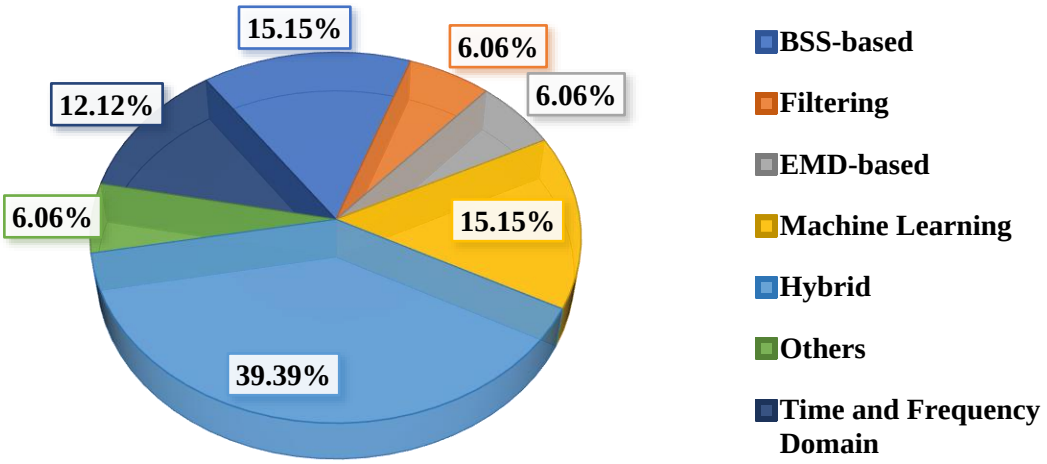


Fig. 1 Pie chart of techniques used in recent high-influential publications.

3. Methodologies

Here we illustrate the basic idea and roll out the latest proposals or applications in each category.

3.1. Blind Source Separation (BSS)

As one of the most basic yet classic techniques for artifact removal, blind source separation aims at the estimation of the signal S with no prior knowledge, linearly transformed with matrix A and usually mixed with noise N [4]. The prerequisite is that the dimensions of the source are no more than the number of channels. Several ways belong to BSS to obtain the reverse transform matrix W and the estimation of S. PCA and ICA are the commonly used ones derived from eigenvalues of the covariance matrix for the first and independent components selection for the other [5]. Another well-known example of canonical correlation analysis is also available by exploiting the maximum correlation between two consecutive samples that are both linearly combined [6], which is implementable considering computation cost.

In terms of recent studies, a combination was proposed using a clustering algorithm partnered with constrained ICA for ballistocardiogram (BCG) artifacts removal, which is the consequence of the cardio activities and the magnetic field causing twisted EEG signals in EEG-fMRI application [7]. Another artifact is the gradient artifact in this scenario, with which Gallego uses average artifact subtraction (AAS) [8]. He also examines different combinations such as AAS-ICA, AAS-OBS, etc. for BCG elimination. In terms of others, Cheng *et al*. propose a combination of singular spectrum analysis (SSA) and second-order blind identification (SOBI) to deal with single-channel artifacts including electrocardiogram (ECG), electromyogram (EMG) and electrooculogram (EOG), which shows validity in the presence of all of which in separate channels simultaneously [9]. In 2020, Li *et al*. used additional sources of EMG for reduction utilizing ICA [10]. The next year, Alturki *et al*. utilized ICA followed by a fifth-order bandpass Butterworth filter as preprocessing for autism diagnosis [11].

3.2. Filtering

While simple single-order FIR or IIR filters are not adequate for complex processing, this category also includes linear filters, like the Wiener filter introduced in [12]. This application assumes that artifacts and EEG signals are linearly coupled with each other. Consequently, a communized multi-input multi-output (MIMO) Wiener filter is designed for the assessment of the artifact. Inside the filter, the parameters are continuously updated according to the Wiener-Hopf equation from measurements [13].

Another exploitation is to evaluate the denoising performance of three filters – the median filter, the Savitzky-Golay filter, and the regularization filter – form smoothing in the presence of noise-mixed EEG data [14]. In this study, Alzahrani *et al*. found that the last one can improve the quality of EEG signals to a relative extent.

3.3. Empirical Mode Decomposition (EMD)

EMD is a well-known method to decompose certain signals into several components, named intrinsic mode functions (IMF). IMFs are signals in which extremes are no more than zero points by one. To extract one IMF, interpolation has to be performed twice, one is between adjacent maximas and adjacent minimas the other. Doing so obtains two envelopes. Subtracting the original signal with the mean of the envelopes, and examining the result corresponding to the property mentioned above, it can be determined whether an extra process on this temporary result should be required or not. If not, then it is an IMF [15]. EMD is a useful tool for time-frequency analysis without Fourier transform to a non-stationary signal [16].

In practice, however, EMD is sensitive to noise and sampling [17]. To address this, additional modified versions of EMD are proposed. For example, one of the derivatives is variational mode decomposition (VMD). Here, the components are complex. Another example is called ensemble EMD (EEMD), in which additive noise helps with the robustness of EMD [18].

In 2018, the usage of VMD with extra hybrid techniques like VMD-PCA and VMD-CCA was applied to evaluate the performance of motion artifacts in EEG data of a single channel, conducted by Hossain [19]. Results indicate that the last one outperforms the rest of the two with at least 0.36dB and 0.61dB differences respectively.

3.4. Time and Frequency Domains

Besides BSS and EMD families, researchers also perform various on the signal itself or its spectrum. Operations include reconstructions, sparse representation, aggregation, regressive, continuous, or discrete wavelet transform (CWT/DWT), moving window block processing, template signal construction, etc. While these measures are not as systematic, well-developed, and widely used, they still have their unique advantages that could be applied alone or in conjunction with other methods. Zebrowska [20] uses moving average subtraction to remove sinuous altering current artifacts which provides ways to expose the covered EEG signals, which results in modification of

filter parameters for precise elimination of artifacts. Tan specifically studied the property of power line artifacts (PLA) and addressed the problem by estimating the harmonic components, combined with sparse representation and spectrum correction [21]. According to the two harmonic maxima in the frequency domain, the compensation signal can be constructed to offset the impact of PLA which remains the clearness of the original signal. Combination and improvement of wavelet transform and mapping methods are also introduced by the work of Dora [22]. Here Dora proposed an advanced usage of wavelets to automatically suppress the artifacts with as little manual intervention as possible. To start with, it is assumed that the brain signals don't abruptly vary in a short period so that artifacts can be targeted in waveforms. With the reference acquired, cumulative density functions can be estimated to map the parameters so that they maximumly suppress the artifacts. In 2021, Li exploited the property of entropy and cross-over phenomenon in sleep and wokeness studies, from which he came up with a new entropy-based method to resolve the problem [23]. Multiscale entropy (MSE) calculates the entropy of a new series derived by averaging consecutive samples within different lengths of region. By combining with instantaneous frequency variation analysis, this proposal shows effectiveness in cross-over artifacts between the sleeping and waking periods.

3.5. Machine Learning (ML)

With the rapid development of AI algorithms, it is reasonable that methods such as deep learning can be applied to artifact removal studies. Machine learning can be subdivided into supervised and unsupervised [24, 25]. The former is also called function approximation, where training data and corresponding output are fed into the model so that the parameters within can update automatically with a given rule of modification. The latter, however, concentrates on discovering the underlying data with no training set given. From this perspective, BSS can be considered as unsupervised learning. With proper introduction and construction of the network architecture, ML-based can offer great accuracy, high flexibility, and convenience.

Latest studies show that an increasing number of people are introducing the ML network for artifact removal. One of the most popular modes, recurrent neural network (RNN), can be found utilized in [26] in the occasion of BCG contamination. Another widespread architecture, convolutional neural network (CNN), can also be found in [27] in terms of eye blink artifacts. To promote its performance for more complex situations, variants based on what is mentioned above are given in various studies. Lopes *et al*. rooted in deep convolution neural network (DCNN) for automatic artifact removal [28]. Furthermore, an advanced multi-module neural network is proposed by Zhang in [29], in which several layers of identical denoising models are in parallel. Each module outputs the filtered signal and estimated artifact. While the signals are summed up, artifacts from the last module will be subtracted with the input to the next module. In [30], a compound architecture based on machine translation is introduced. This model consists of adaptive modules including a discriminator, encoder, attention, and decoder. What's more, this work illustrates an advanced module-gated recurrent-based Multi-type Artifact Removal algorithm for Single-Channel (GRU-MARSC)-to focus closest and most possible artifact feature, which reduces the removal cost and improves high accuracy.

3.6. Hybrid

Compared with the review of 2019, it can be discovered that the compound usage of multiple techniques is on the rise, which indicates that families of techniques like BSS and EMD are not separated from others. Instead, several trials have been found in recent studies that employ methods from numerous categories.

One of the most cited and highly influencing articles is the Harvard Automated Processing Pipeline for EEG (HAPPE) proposed in [31]. This offers a normalized yet applicable for all artifacts. It comprised the usage of filtering, sub-selection, wavelet-enhanced ICA, interpolation, etc., with seven layers of dissimilar modules. This work was introduced in 2018, and recent time has witnessed advanced pipeline for auto processing, such as the HAPPE in low electrode EEG (HAPPILEE)

pipeline proposed in 2021, which optimize the overall performance under low concentration of data [32]. Another instance is the Maryland Analysis of Development EEG (MADE) pipeline, which indicates robustness for distinct systems, people, recorded time as well and the extent of degradation by artifacts [33].

When it comes to other hybrid methods of artifact removal rather than sophisticated block diagrams, much simpler solutions were given. For instance, Teng *et al*. [34] take EEMD and ICA for EEG signals in multiple channels, proving promising for eye blink artifacts. Liu adopts CCA and the Fast Multivariate EMD (FMEMD) for muscle artifacts [35]. Yan and Wu [36] utilized short-time Fourier transform (STFT), EMD in two dimensions, and non-local means (NLM) to constrain the impact of noise and show considerable results. Zangeneh takes three main steps SOBI, SWT, and ML, whose results show average precision as high as 97% [37]. Rusiniak *et al*. combine PCA with surrogate spatial filtering (PCA-S), which outperforms traditional BSS methods including OBS, and OBS-ICA in terms of the quality and features of the signals [38, 39]. Tamburro *et al*. propose a novel method for the automatic removal of cardiac interference (ARCI) which originated from the Fingerprint Method in [40] and associates with ICA in [41] and validify the effect of this approach in the later publication of [42]. The proposal is compared with experts' identification, which gives out the answer as "no" to concerns over loss of brain dynamics. Another study is conducted in [43] for multi-channel occasions, where spatial filtering and tunable-Q wavelet transform (TQWT) are jointly applied in for cortical stimulation artifacts. Spatial filtering includes widely used ones like BSS, filtering, and the wavelets in TQWT are derived from the structure of an LPF and HPF. For more recent ones, Malghan eliminates noise with improved variational mode extraction (IVME) merged with a Heap-Based optimization algorithm (HBO), followed by automatic wavelet thresholding which relies on the interval (AWIT) [44]. While HBO is applied for the objective function defined from the entropy spectrum, IVME obtains components with specific frequencies, and AWIT suppresses non-linear noises.

4. Conclusion

EEG signals can be polluted due to the effect of artifacts due to different causes. This work introduces the publications to date, categorizes them according to their essence of methodology, and offers a general summary. The review of the recent most influential publications shows that conventional methods for removing artifacts are being improved and modified, which also indicates that a nonidentical separation theory with an essentially dissimilar mathematical model has not yet been proposed. Also, the number of methods based on machine learning is on the rise. This may glow with great vitality with the powerful support of hardware technology and the rapid development of the architecture of algorithms. Moreover, although we are witnessing advanced algorithms or systems of reducing typical artifacts like EMG and ECG. Newly developed amalgamative ways combining different ideas and algorithms, and the use of standardized pipelines show that people are looking for a general and universal solution that can remove all artifacts globally. However their effectiveness, robustness, and flexibility still require further examination. For future applications in more realistic and practical situations, methods that assist with machine learning for more common scenarios in daily life may be a great trend.

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