Artifact Detection and Correction in EEG data: A Review

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Abstract—Electroencephalography (EEG) has countless applications across many fields. However, EEG applications are limited by low signal-to-noise ratios. Multiple types of artifacts contribute to the noisiness of EEG, and many techniques have been proposed to detect and correct these artifacts. These techniques range from simply detecting and rejecting artifact ridden segments, to extracting the noise component from the EEG signal. In this paper we review a variety of recent and classical techniques for EEG data artifact detection and correction with a focus on the last half-decade. We compare the strengths and weaknesses of the approaches and conclude with proposed future directions for the field.

I. INTRODUCTION

Electroencephalography (EEG) is a non-invasive, inexpensive, and portable neuro-imaging technology, but the low signal-to-noise ratio of EEG limits its ease of adoption and use for the research and commercial communities alike. The low signal-to-noise ratio of EEG is due, in part, to a variety of artifacts including ocular artifacts from blinks and eye movements and muscle artifacts from movements. While EEG data is affordable to collect, it is challenging to use in practice because artifacts correction is a necessary prerequisite for meaningful use.

To reduce the human labor associated with EEG experimentation (and the requisite data cleansing) researchers have developed several methods for automated artifact detection. Once an artifact has been detected, the corrupted segment may be discarded but discarding segments introduces discontinuities to the signal that may limit its applications. To circumvent discontinuities, artifact correction techniques may be utilized to "correct" the signal. Implementing effective strategies for artifact detection and correction requires careful review of approaches scattered across the scientific literature. In this review, we highlight the key research contributions in the EEG artifact detection and correction domain over the last 7 years, and identify promising directions for further research and development efforts.

II. DEFINITION OF ARTIFACT

For the EEG community, an "artifact" refers to a diverse set of signal distortions that span spatial, frequency and temporal scales [14]. While different taxonomies of artifacts have been proposed [14], the exact distinction between signal and artifact is often dependent on the specific purposes of those collecting the data. For instance, muscle artifacts are unwelcome in a motor-imagery Brain Computer Interface (BCI) application, but are useful for tasks such as sleep stage identification [15]. Given the variety of phenomena that could be classified as an artifact for any given EEG use-case, it is not surprising that artifact detection algorithms are narrowly-focused on correcting the intruding artifact in a specific context [1]. An alternative approach argues that a distortion to an EEG segment is an artifact if and only if the distortion negatively impacts the performance of a downstream task [11].

III. SCOPE OF REVIEW

This review includes algorithms for artifact detection and correction using EEG data, alone. That is, we do not discuss algorithms that rely on external signals (e.g. electrooculography). Furthermore, we exclude research focused on electrode ‘pops’ or other spatially localized artifacts as their unique characteristics enable ease of detection by simple unsupervised and self-supervised techniques [16]. Finally, for the sake of brevity, when a group of papers constitutes a sequence of incremental improvements, we select only the work which presents the accumulation of that line of research [17], [10]. Table I provides an overview of the literature surveyed in this review.

A. Removal vs. Correction

This review distinguishes between two approaches: artifact removal and artifact correction. For an algorithm to perform correction (rather than removal) it must have access to an artifact free version of the EEG waveform to be used as ground truth for correcting an artifact ridden version of that same waveform. Note that this necessitates that artifact correction algorithms are trained on datasets with simulated artifacts (for instance see the data-set proposed by [13]).

B. Metrics

The performance of artifact detection algorithms are often measured using manually annotated EEG signals. Common metrics to evaluate artifact detection methods include the F1 score, accuracy, sensitivity, specificity, Area Under the Receiver Operator Curve (AUC), and Cohen’s Kappa (intrarater reliability). For the purpose of comparing performance in this review, we standardized these metrics when possible. For instance, if an author did not report the F1 score, we attempted to derive it from the other metrics [8].

For artifact detection, we compare algorithms using several common performance metrics. We note that not all metrics are equally valid for evaluating EEG artifact detection algorithms. The F1 score and accuracy are appropriate for the assessment of tasks with balanced outcome class labels, which is not common in artifact annotation settings; a
classifier graded on an unbalanced dataset may achieve a high accuracy but suffer from a high false negative rate.

Artifact correction algorithms are more challenging to assess compared to detection algorithms as (barring simulated data) the ground truth is unknown. When artifacts are simulated, and access to the artifact free waveform is available, metrics such as normalized mean square error (NMSE) and root mean square error (RMSE) are used [12], [13]. When the data is not simulated the same metrics are calculated using artifact free EEG data collected under similar circumstances (i.e. stimuli and task) [8]. The signal-to-noise ratio (SNR) between clean and noisy EEG post artifact removal is another popular metric [6]. Finally, some researchers use the improvement in downstream task performance as a measure of the reconstruction fidelity; for instance, artifact removal was demonstrated to improve stimuli decoding and visual-evoked potentials recognition [11], [10].

C. Datasets

Table I lists a summary of investigations conducted for the purpose of developing algorithms for artifact detection and correction. We note that investigators typically evaluate their approaches on data they have collected themselves, as opposed to a standard community benchmark dataset; this highlights a larger issue in the EEG research community around data sharing practices. When data is shared, it is often to study a particular downstream task, so to facilitate this end, artifacts are often removed which renders the dataset irrelevant for the purpose of artifact detection research. For papers surveyed in this review, only a few made their datasets publicly available [5], [7], [9], [11].

IV. ARTIFACT DETECTION METHODS

Various machine learning and statistical approaches have been applied to the domain of artifact detection. We elaborate on these methods below.

A. Hand Crafted Methods

The BLINK algorithm was tailor-made to detect the specific signal characteristics of artifacts caused by eye blinks. Like many hand crafted methods, this approach performs well for the specific task it was engineered to accomplish, but can not be easily extended, tuned, or adapted to detect other types of artifacts [7].

B. Signal Decomposition Methods

Blind source separation methods, most prominently Independent Component Analysis (ICA), treat EEG as a composite signal; ICA decomposes EEG signals into their constituent signal components from which an expert may identify and remove artifact components. While there are rules-of-thumb to distinguish artifact from signal components (for instance, higher power aggregates in frontal areas of scalp maps for blinks), expert annotation is still often required. One notable exception to this is the work of Shamlo

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**Table I**

| Paper | Artifact | Type | Datasets | Method | Requirements | Performance |
|-------|----------|------|----------|--------|--------------|-------------|
| [1]   | Blinks   | D    | 4256 trials† | ICA    | A dataset of 3452 ICA scalp-maps | > 0.80 AUC |
| [2]   | Blinks Muscle | D | 47752 trials† 1955 Blinks 4203 Muscle Mov. | Supervised learning algorithms | Requires labeling | 0.98 F1 |
| [3]   | Muscle   | R    | ¶        | Hand Crafted EEMD | Uses expert knowledge | .83 F1 |
| [4]   | All      | R    | ¶        | LDA, SVM, KNN, ICA | Requires labeling | < 0.50 F1 |
| [5]   | All      | D    | ¶        | CNN classifier | Requires labeling | 0.92 F1 |
| [6]   | All      | R    | 2 new datasets real and simulated† | MWF | Requires labeling assumes stationarity | 6.20 SNR |
| [7]   | Blinks   | D    | ¶4 new datasets 2350 blinks | Hand Crafted | Assumes artifact frequency | > 0.94 F1 |
| [8]   | Blinks   | R    | ¶12000 trials 1000 Blinks | SVM Autoencoder | Requires labeling | > 0.98 F1 .024 RMSE |
| [9]   | Blinks, Muscle, Heart Line, Channel | D | ¶6352 subjects | ICA CNN classifier | Labeling of ICA components | 0.80 F1 (multi-class) |
| [10]  | Blinks   | R    | ¶2 new dataset simulated and real | ICA with ASR | Labeling of ICA components | Downstream ERP recognition |
| [11]  | All      | R    | ¶2 new datasets 4578, 4569 trails 628, 570 artifacts | Classical classifiers and Autoencoder | Assumes artifacts are uncommon | 0.54 F1, 0.45 Kappa Downstream classification |
| [12]  | Blinks   | R    | modified dataset EEGLAB data with simulated blinks | ICA, SVM and Autoencoder | Uncorrelated signal and noise | 0.97 F1 .04 NMSE |
| [13]  | Blinks Muscle | C | modified dataset with simulated artifact | Autoencoder | Simulates only specific artifacts | 0.56 RRMSE |
et al., who side-stepped the need for an expert annotator by collecting thousands of scalp maps of blink artifacts to contrast new EEG segments against [1].

C. Supervised Approaches

Supervised classification approaches including Support Vector Machines (SVM), Decision Trees, and K-nearest neighbors (KNN) have been applied for a variety of EEG artifact detection problems. Deep learning and Neural Network methods are a relatively recent development in the field of EEG artifact detection. Multiple recent efforts have applied Convolutional Neural Networks (CNN) to EEG by representing data as an $n \times t$ image of $n$ channels and $t$ samples. Nejedly et al. used a CNN in conjunction with fully automated image processing procedures to automatically detect artifacts in intracerebral EEG data [5]. Transfer learning has also been used to improve the performance of network models previously trained on different datasets [5]. Ultimately, supervised classifiers have been shown to effectively discriminate artifact from signal segments [4], [8], but require annotated artifact data to do so, which is not commonly available for many EEG datasets.

D. Unsupervised Approaches

Sadiya et al. proposed a general-purpose artifact detection algorithm [11]; their method extracted 58 different EEG features that are commonly used in EEG research and prognostication, and made the assumption that the frequency of artifacts in the datasets was relatively low. While, this assumption may not always be true (for instance, seizure detection), it is usually valid. The authors benchmarked multiple unsupervised methods. For instance, an auto-encoder was trained to reconstruct EEG waveform segments. Assuming artifact are infrequent, the auto-encoder minimizes the reconstruction error for artifact free trials, hence high reconstruction error is taken as indicative of an outlier EEG segment likely to be an artifact. Their results showed artifact detection rates comparable to the inter-annotator agreement reported in the literature, but as expected, unsupervised algorithms are outperformed by methods tailor-made to detect a given artifact type (Table 1).

E. Hybrid Approaches

Hybrid methods that use deep learning classifiers in conjunction with other methods have shown great promise. ICLabel is a recently available artifact rejection plugin for EEGLab that uses a CNN to label the components of the ICA decomposed waveform [9]. The classifier distinguishes between seven different artifact types with a binary accuracy (artifact vs signal) of 0.83. Like other ICA based algorithms, ICLabel is capable of online artifact rejection.

V. Artifact Removal and Correction Methods

Detecting and excluding artifact ridden trails allows researchers access to clean data. However, these trials could constitute a non-trivial portion of the collected data, and rejecting them may introduce discontinuities into data that is fundamentally temporal in nature. Recent research efforts have focused on approximating an artifact free version of the affected segment, instead of discarding it all together. It is important to note that all artifact removal methods discussed below are supervised, even when constituting a component of a larger unsupervised pipeline.

A. Signal Decomposition Methods

As previously stated, ICA decomposes EEG signals into their constituent components from which noise components may be identified. A natural extension of the detection algorithms discussed above is to reconstruct the EEG signal from all but the identified noise components. Gilbert et al. trained several classifiers (LDA, SVM, KNN) to distinguish between signal and noise independent components [4], and as previously mentioned, [9] trained a CNN classifier to distinguish between noise and signal components. Notably, these methods involve some global loss of information when the signal is reconstructed [12].

Another approach to blind source separation is Artifact Subspace Reconstruction (ASR) which learns statistical characteristics of the components resulting from Principal Component Analysis (PCA). While the performance of ASR and ICA based methods are comparable, the former is faster and less computationally demanding, and is therefore more suitable for online artifact correction [10].

Extended Empirical Mode Decomposition (EEMD) has also used for EEG artifact removal [3]. Empirical mode decomposition methods can be used as filters but are not strictly in the same category. EMDs decompose signals into a special class of generating functions that maximizes the signal-to-noise ratio of the reconstruction. While EMDs might appear reminiscent of ICA, the nature of the decomposition is different. ICA decomposes the data for all EEG channels simultaneously, while EMD and the other filtering methods decompose the signal at each channel separately.

B. Filter-based Methods

In signal processing, filters are basic sequence-to-sequence elements that suppress unwanted temporal phenomenon. The Multi-Channel Wiener Filter (MWF) has been used to great effect in audio and speech processing; Wiener filters use labeled examples to estimate parameters of the signal and noise waveforms such that that noise waveform may be filtered out while the NMSE between a clean signal and its output is minimized. The amount of labeling required to use MWF is minimal and an EEGLab plugin is publicly available [6]. MWF assumes stationary of the EEG and noise profiles but to be fair, many simple classifiers make a similar assumption. With sufficient depth, neural encoder-decoder models can learn to correct multiple artifacts drawn from different distributions.
C. Supervised Approaches

Artifact removal with neural networks is a recent development that was been made possible with breakthroughs in sequence-to-sequence modeling tasks using encoder-decoder neural network architectures. Since the ground truth is not usually available, researchers use noisy trials as the input sequence to the encoder-decoder model and artifact free trials as the target sequence [8]. To facilitate work in artifact correction, EEGdenoiseNet was recently published as a benchmarked data set of simulated ocular and muscle artifacts [13]. The package provided by the authors allows for the simulation of various artifacts at various signal-to-noise ratios. The authors implemented fully-connect, convolutional, and recurrent neural networks to benchmark the data-set.

D. Unsupervised Approaches

As discussed, Sadiya et al. suggested an unsupervised approach for artifact detection. Assuming a low false positive rate, the authors used the trials marked as artifact free to train an CNN to reconstruct EEG segments using surrounding samples. The trained network was then used to reconstruct artifact ridden segments. By training with artifact free trials, the method ensures that the reconstructed signal approximates an artifact free signal. While the artifact removal component itself was supervised the pipeline as a whole does not require any labeling (due to the artifact detection being unsupervised). Note that this same approach could be used with any other supervised artifact removal component such as [8], [6]. This approach remains highly limited by the low accuracy of unsupervised artifact detection (Table I).

E. Hybrid Methods

Phadikar et al. suggested a hybrid model that uses SVMs to detect noise components in the ICA deconstructed signals and a denoising autoencoder to remove artifacts from the ICA components rather than the raw EEG [12]. By denoising the ICA components, instead of excluding them from the reconstruction all together, the reconstruction was found to be more accurate.

VI. CONCLUSION

In this review, we provide a succinct overview of EEG artifact detection and correction methods, with a focus on the last 5 years of research. We reviewed many more papers than formally discussed in this article; indeed, there has been an increased interest in artifact detection and removal as EEG devices become more prevalent in multiple fields.

As evident from Table I the research community is in dire need for a standardized metric, database, and terminology surrounding the EEG artifact detection task, especially if the goal is to produce usable application that will generalize to multiple datasets, and heterogeneous tasks. The more recent entries in Table I imply a growing popularity of deep learning techniques comes at the expense of traditional approaches and expert knowledge. However, we note that recent papers successfully drew on the rich history and knowledge developed within the EEG preprocessing community to build hybrid approaches that synthesize deep learning, ICA frameworks [12], or features borrowed from EEG prognostication [11]. We believe that hybrid frameworks are an interesting future direction of work in this domain and uniquely situated to combine the strengths of multiple approaches that will advance the current state-of-the-art.

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