International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-11 Issue-6, March 2023

A Review on Detection and Correction of Artifacts from EEG Data

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Abstract: Electroencephalography (EEG) offers a wide range of uses in a variety of industries. Low SNR (signal to noise ratios), nevertheless, limit EEG applicability. EEG noise is caused by a variety of artifacts and numerous strategies have already been developed to identify and eliminate these inconsistencies. Various methods differ from merely identifying and discarding artifact ridden segments to isolating the EEG signal's noise content. With an emphasis on the previous half decade, we discuss a range of contemporary and traditional strategies for EEG data artifact recognition and removal. We assess the approaches' merits and drawbacks before proposing potential prospects for the area.

Keywords: Electroencephalography (EEG), Artifact, Artifact Removal, Artifact Correction

I. INTRODUCTION

Although electroencephalography (EEG) is a "non-invasive", low-cost along with widely available "neuro-imaging" method, its poor SNR makes it challenging to embrace and use in both research and commercial settings. EEG has a low SNR due to a variety of aberrations, such as ocular aberrations from blinks, as well as eye motions as well as muscular artifacts accompanying activities. Although EEG information is inexpensive to gather, it is exigent to employ in process due to the need to remove artifacts before it can be meaningfully employed. Investigators had also devised a number of methods for automatically detecting artifacts in EEG tests, reducing the amount of human labor required as well as the associated record clearing. The contaminated section may also be eliminated once an artifact has been recognized, but eliminating sections produces interruptions in the signal, which may restrict its usefulness. Artifact rectification approaches can be used to "correct" the signal in order to prevent interruptions. Applying efficient artifact identification and rectification solutions necessitates a thorough analysis of methodologies spread throughout the research journals. In this study, we emphasize significant research accomplishments in the domain of EEG artifact identification and rectification over the last seven years, as well as prospective research and development directions.

Manuscript received on 24 February 2023 | Revised Manuscript received on 28 February 2023 | Manuscript Accepted on 15 March 2023 | Manuscript published on 30 March 2023.
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II. EEG ARTIFACTS

The EEG research group uses the term "artifact" to designate a wide range of pattern anomalies that span temporal, spatial including time domains. [15]. Despite the existence of alternative artifact classifications [15], the specific demarcation amongst signal as well as artifact is typically dictated with the purpose of those collecting the data. Muscle artifacts, for example, are undesirable in a "motor imagery Brain Computer Interface (MI-BCI)" implementation although valuable in sleep pattern detection applications. [16]. Because there are so many things that can be classified as an artifact in each EEG demo, it's no wonder that artifact identification strategies are solely concerned with removing the intruding artifact [2]. According to one school of thought, an EEG fragment aberration is an artifact if or even if it has a negative impact on future task performance. [1, 12].

2.1. Characteristics of EEG

Electroencephalography is a method of measuring voltage variations in brain activity by recording the brain's endogenous electrical activity. The frequency range of EEG signals is 0.01 to 100 Hz, and they can be divided into five frequency bands including four basic groupings, as shown in Table 1.

Table 1: Frequencies of Basic Brain Waves

Name of Band	Frequency (Hz)	Elucidation
Delta	Less than 4	Profound Sleep
Theta	4 to 8	Meditation and a Relaxed State
Alpha	8 to 13	Consciousness in a Relaxed State
Beta	13 to 30	Thinking Actively

2.2. Types of EEG Artifacts

When EEG data is acquired using recording equipment, signal artifacts are more visible. These artifacts can corrupt EEG data. To properly eradicate the artifacts or noise in this scenario, a thorough grasp of the many types of artifacts is essential. Noise in the surrounding, experimental errors and physiological artifacts all create unwanted signals known as artifacts. Furthermore, external elements such as the surroundings and experimental error are classed as extrinsic artifacts, physiological artifacts, on the other hand, are categorized as intrinsic artifacts. The examples of intrinsic artifacts includes eye blink, muscle activity, heart beat. Figure 1 depicts the three most common physiological artifacts found in the literature. Since the frequency of these kinds of distortions differs from the frequency of desired signals, they may be removed with a simple filter.

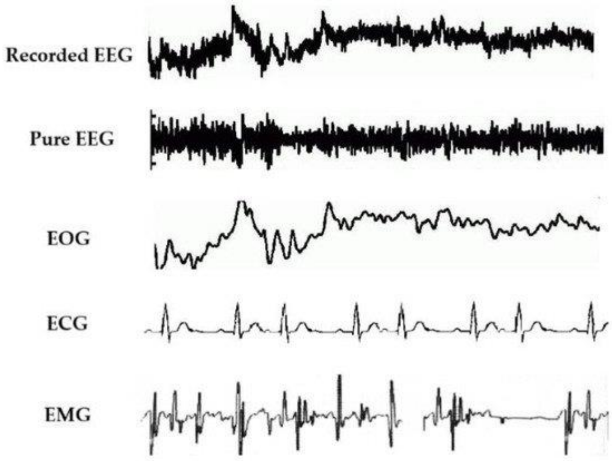

Fig. 1. Types of EEG Artifacts

III. SCOPE OF REVIEW

This research provides techniques for detecting and correcting artifacts using only EEG data. That is, strategies that depend on extrinsic signals such as electro-oculography are not discussed. Additionally, exploration on electrode 'pops' or related spatially focused artifacts is excluded since their distinctive qualities make them easy to detect using basic unsupervised and self-supervised algorithms [16]. Furthermore, when a collection of publications represents a series of progressive advancements, we identify only the contribution that represents the culmination of that stream of thought for the purpose of simplicity [18, 11]. The literature examined in this study is reported in Table 2.

Table 2: Literature Assessment by Year of Survey

Literature No.	Type of Artifact	Approach used	Requirements	Performance
[2]	Eye-Blink	Independent Component Analysis	ICA Dataset	Greater than 0.8 AUC
[3]	Eye-Blink, Muscle	Supervised Learning Approaches	Labeling Required	0.99 F1
[4]	Muscle	Enhanced Empirical Mode Decomposition	Need Expert Acquaintance	0.8 F1
[5]	All	Hybrid	Labeling Required	Less than 0.49 F1
[6]	All	CNN Classifier	Labeling Required	0.91 F1
[7]	All	Multi Channel Wiener Filter	Labeling Required	Greater than 0.93 F1
[8]	Eye	Hand Crafted	Labeling Required	Greater than 0.98 F1
[9]	Eye	Auto-Encoder	Labeling Required	0.79 F1
[10]	Eye-Blink, Muscle, ECG, Power-line	Hybrid	ICA components	Downstream ERP Identification
[11]	Eye-Blink	Hybrid	ICA components	0.54 F1
[12]	All	Auto-Encoder	Uncommon artifacts	0.97 F1
[13]	Eye-Blink	Hybrid	Uncorrelated Signal and Noise	6.2 SNR
[14]	Eye-Blink, Muscle	Auto-Encoder	Only Specific Artifacts are Simulated	0.55 RRMSE

3.1. Removal Versus Correction

Artifact elimination and artifact rectification are the two methodologies discussed in this paper. In order to achieve rectification, an algorithm should be having the ability to an "artifact-free" edition of the EEG pattern to use like underlying data in favor of rectifying an outlier rendition of the similar waveform instead of eradication. It's worth mentioning that this involves the development of artifact rectification methods on records with synthetic artifacts as an example; observe [14]'s data set.

3.2. Metrics

Artifact detection methods are frequently evaluated using human labeled EEG recordings. The "F1 score, accuracy, sensitivity, specificity, AUC and Cohen's Kappa" are all common metrics used to evaluate artifact detection algorithms. When possible, we standardized these indicators in order to compare effectiveness in this evaluation. We endeavored to estimate the F1 score from the other measures if a researcher did not investigate it [1, 8]. We evaluate techniques for artifact identification using a range of reliability criteria. It is indeed worth noting that not all parameters for measuring EEG artifact identification methods are created equal. The F1 score and effectiveness are suitable for problems with neutral result different classifiers, which are typical in artifact annotation settings; a classifier evaluated on an asymmetrical dataset may have a high false negative rate but have a high precision. Because the classification algorithm is unclear, artifact restoration approaches are much more difficult to judge than detection procedures. While artifacts are modeled and access to the artifact-free waveform is accessible, effectiveness measurements such as the normalized mean square error (NMSE) as well as the standard deviation are employed. Whenever the information is not really generated, the similar parameters are derived utilizing artifact free EEG data taken under identical conditions [9]. The SNR between pure and chaotic EEG is additional important statistic after artifact reduction. [7].

Retrieval Number: 100.1/ijrte.F74970311623
DOI: 10.35940/ijrte.F7497.0311623
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Furthermore, many researchers employ future objective execution as a criteria for restitution accuracy; for example, artifact removal has been shown to improve information processing and visual triggered potential identification. [11, 12].

3.3. Datasets

Table 2 summarizes the researches carried out in order to create strategies for artifact identification and rectification. We see that researchers often assess their strategies using information they have gathered themselves rather than a uniform community benchmark dataset; it thus reflects a greater concern in the EEG research field regarding information exchange procedures. Whenever information is distributed, it is frequently to investigate a specific downstream goal; as a result, artifacts are frequently eliminated, rendering the dataset useless for artifact recognition investigation. Only a few of the articles in this assessment rendered their information freely accessible [6, 8, 10, 12].

IV. ARTIFACT DETECTION METHODS

A range of machine learning as well as quantitative methodologies has been utilized in the field of artifact identification. We will go over each of these strategies in more detail beneath. [15, 16]

4.1. Hand Crafted Methods

To perceive the signal qualities of eye blink artifacts, the BLINK technique was designed primarily. This methodology, like other handcrafted approaches, works effectively for the purpose it was designed to do, but it cannot always be improved, adjusted or modified to identify various forms of artifacts [8,17].

4.2. Signal Decomposition Methods

EEG is treated as a blended signal in blind source separation approaches; ICA functions by separating EEG signals down into their core signal constituents, allowing an analyst to discover and eliminate artifacts. Despite the existence of several criteria for distinguishing artifact from frequency constituents, such as larger amplitude averages in the frontal regions of scalp rhythms for blinks, expert interpretation is usually necessary. Shamlo et al's work which gathered thousands of brain combinations of eye movement pattern artifacts to compare additional EEG sections without the requirement for an experienced annotator is another prominent example. [2,18].

4.3. Supervised Methods

"Support Vector Machines (SVM), Decision Trees, and K-nearest neighbours (KNN)" are examples of supervisory classification algorithms that have been used to handle a range of EEG artifact identification challenges. In the realm of EEG artifact identification, deep learning as well as neural network approaches are a comparatively new discovery. To depict EEG data, a convolutional neural network (CNN) has been used as a p x q representation with p channels and q samples in a number of recent studies. Nejedly et al. used a CNN in conjunction with fully automated image processing techniques to detect artifacts in intra-cerebral EEG data [6]. Deep learning was often employed to perk up the efficiency of "network models" created on a range of data-sets [5]. Finally, trained systems were proven to differentiate artifact from frequency sequences accurately [5, 9], but they necessitate tagged artifact information, that is not easily accessible for numerous EEG databases.

4.4. Un-supervised Methods

Sadiya et al. described the fundamental artifact identification algorithm [12], which returned 58 distinct EEG variables that are regularly used in EEG inquiry and future predictions, presuming that the number of artifacts in the datasets has greatly decreased Although this presumption is just not correct for example, detection of seizure), it is indeed frequently correct. Multiple unsupervised approaches were tested by the researchers. EEG waveform fragments were taught to an auto-encoder, for example. Because artifacts are rare, the auto encoder reduces the restoration error for "artifact-free trials", and a substantial reconstruct error is regarded as a symptom of an artifact-causing aberrant EEG segment. Their findings revealed artifact identification levels that were equivalent to inter-annotator contract published in the research; however unsupervised algorithms were surpassed by approaches tailored to identify a specific artifact type, as anticipated in Table 2.

4.5. Hybrid Approaches

Hybrid approaches that combine deep learning algorithms with conventional strategies have demonstrated to be quite promising. IC Label is a new artifact elimination module for EEGLab1 that labels the constituents of the ICA deconstructed waveform using a CNN [9]. With a binary efficiency of 0.83 (artifact versus signal), the classifier can discriminate amongst seven alternative artifact kinds. IC Label, like other ICA-based techniques, may reject artifacts in real time.

V. ARTIFACT REMOVAL AND CORRECTION METHODS

Researchers can get proper results by identifying and abolishing artifact ridden routes. Nonetheless, such trials could account for a large portion of the data collected, and removing them could result in gaps in data which is primarily periodic in nature. Current findings have centered on calculating an "artifact-free" adaptation of the afflicted area rather than rejecting it completely.

5.1. Signal Decomposition Methods

As aforementioned, ICA breaks down EEG signals into their fundamental sources that can then be used to identify distortions. The above-mentioned detection methods logically lead to the reconstruction of the EEG information with everything but the additive noise seen. Gilbert et al. [5] used numerous classifiers "(LDA, SVM, KNN)" to differentiate among signal in addition to aspects which are noise independent, while [10] used a CNN classifier to make a distinction among noise plus signal mechanism, as mentioned earlier. Interestingly, when the signal is regenerated, these approaches result sometimes in temporal data lost [13].

Artifact Subspace Reconstruction (ASR), essentially examines statistical features of constituents generated by Principal Component Analysis (PCA), is another method for blind source separation. While both ASR and ICA-based techniques are equally successful, the latter is simpler and requires less computer power, making it better suited for online artifact elimination. [11]

EEG artifact removal has also been done using Extended Empirical Mode Decomposition (EEMD) [4]. Although empirical mode decomposition methods can be employed as filters, they do not fall into the similar genre.

EMDs break signals into a certain type of producing feature that optimizes the reconstruction's SNR. Although EMDs look to be similar to ICA, the breakdown process is distinct. Whereas EMD as well as other filtering algorithms deconstruct the signal at every channel independently, ICA breaks down the information for all EEG channels at the same time. Figure 2 depicts EEMD process.

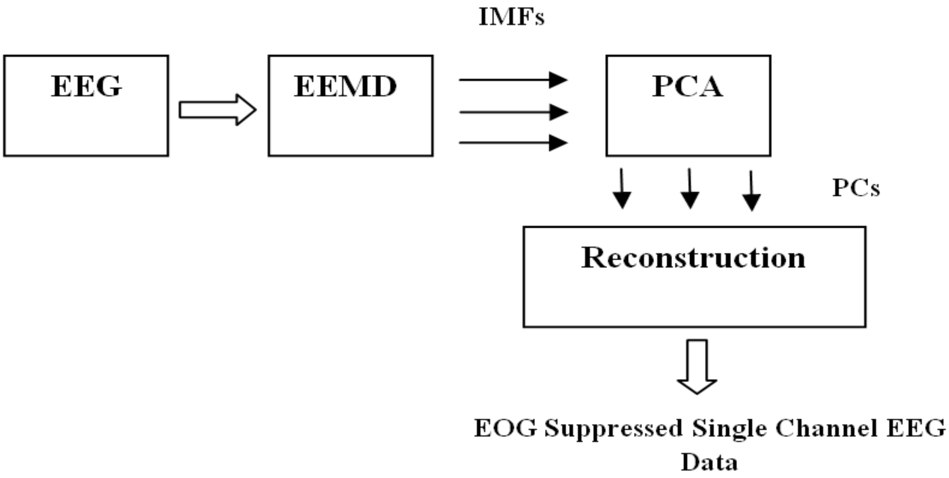

Fig. 2. Block Diagram of Enhanced Empirical Mode Decomposition

5.2. Filter Based Approached

Filters are fundamental signal processing segment features that reduce unwanted temporal occurrences. Wiener filters anticipate signal and noise propagation characteristics using labeled samples, allowing the noisy amplitude to be filtered out while the NMSE between the pure signal and its conclusion is reduced. To use MWF, just basic labeling is required, and an EEG Lab plug-in is readily accessible. [7]. The EEG and noise profiles are assumed to be stationary by MWF; however numerous simple classifiers do as well. Neural encoder-decoder models with enough depth can learn to fix a variety of artifacts from various backgrounds. The schematic diagram of MWF is shown in Figure 3.

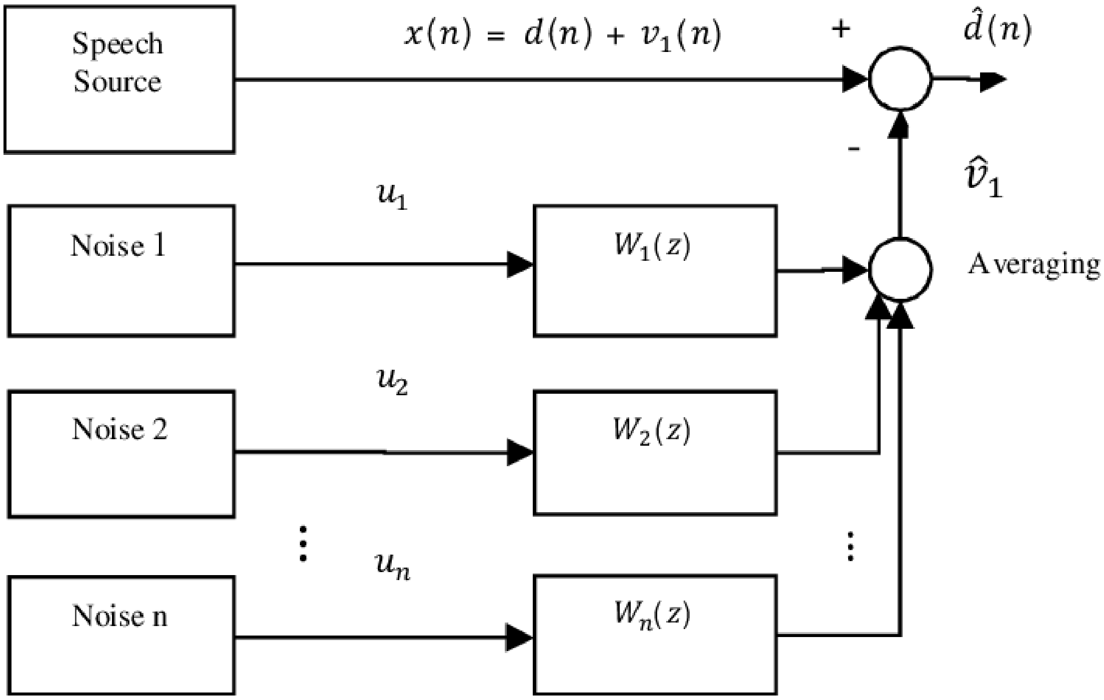

Fig. 3. Block Diagram of Multi-Channel Wiener Filter

Retrieval Number: 100.1/ijrte.F74970311623
DOI: 10.35940/ijrte.F7497.0311623
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5.3. Supervised Methods

Artifact eradication with neural networks is a relatively new innovation, facilitated by advances in encoder decoder neural network topologies for sequence to sequence modeling problems. Investigators employ noisy samples as the original signal for the encoder decoder framework and artifact-free trials as the goal sequence because the classification process is so sparse [9]. *EE Gdenoise Net*, a standardized data set containing synthetic ocular and muscular artifacts, was subsequently provided to aid efforts in artifact rectification [13]. The authors' programme enables for the modeling of numerous artifacts at different SNR. To examine the data, the authors used densely integrated, recurrent and repeated neural networks.

5.4. Unsupervised Methods

Sadiya et al. proposed an unsupervised approach for artifact recognition, as previously mentioned. The artifact-free trials were utilized to teach a CNN to reconstruct EEG segments using nearby data with high accuracy. The artifact-ridden areas were then recreated using the trained network. The technique assures that the restored information appears like an artifact-free signal by conditioning with "artifact-free" trials. Despite the fact that the artifact eradication phase was supervised, the workflow overall did not require labeling because of the unsupervised artifact detection. This method might also be applied to any other supervised artifact elimination feature, such as [7, 9]. The exactness of unsupervised artifact identification limits this strategy significantly as depicted in Table 2.

5.5. Hybrid Methods

According to Phadikar et al., SVMs are implemented to recognize noise constituents in the ICA reassembled signals, and a de-noising auto encoder rather than the raw EEG, is used to remove artifacts from the ICA components. [13]. The reconstruction was shown to be more precise by de-noising the ICA components rather than eliminating them entirely from the reconstruction.

VI. RESULTS AND DISCUSSION

As illustrated in Table 2, the field of EEG artifact identification research is in critical need of a uniform metric, database, and terminology, particularly unless the objective is to generate an useful feature which can be applied to a wide range of information as well as activities. The increasingly frequent items in Table 2 suggest that deep learning approaches are gaining prominence at the cost of traditional methodologies and domain expertise. Recent articles, however, have effectively built hybrid techniques that integrate deep learning, ICA frameworks [13] or characteristics derived from EEG predications [12] by drawing on the rich experience and expertise accumulated inside the EEG preprocessing community. Hybrid frameworks, we suggest, offer an exciting future avenue of research in this field, since they are ideally positioned to combine the capabilities of various methodologies to advance the existing state.

VII. CONCLUSIONS

We give a quick overview of EEG artifact identification and rectification approaches in this article, with an emphasis on the last five years of investigation. We looked at a lot more publications than we did in this paper; in fact, as EEG monitors become more used in various sectors, there has been a surge in concern in recognition and elimination of artifact.

DECLARATION

Funding/ Grants/ Financial Support	No, I did not receive.
Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	The present article has been submitted having equal contribution from both the authors.

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