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A Review on Detection and Correction of Artefacts 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 ratio), however, limits EEG applicability. A variety of artefacts cause EEG noise, and numerous strategies have already been developed to identify and eliminate these inconsistencies. Various methods differ from merely identifying and discarding artefact-ridden segments to isolating the noise content of the EEG signal. With an emphasis on the previous half decade, we discuss a range of contemporary and traditional strategies for EEG data artefact recognition and removal. We assess the merits and drawbacks of the approaches 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, and 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, and muscular artefacts accompanying activities. Although EEG information is inexpensive to gather, it is essential to employ it in processing due to the need to remove artefacts before it can be meaningfully analysed. Investigators had also devised several methods for automatically detecting artefacts in EEG tests, thereby reducing the amount of human labour required, as well as the associated record clearing. The contaminated section may also be eliminated once an artefact has been identified, but eliminating sections produces interruptions in the signal, which can restrict its usefulness. Artefact rectification approaches can be used to "correct" the signal to prevent interruptions. Applying efficient artefact identification and rectification solutions requires a thorough analysis of methodologies presented in 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.

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II. EEG ARTIFACTS

The EEG research group uses the term "artefact" to designate a wide range of pattern anomalies that span temporal, spatial, and time domains. [15]. Despite the existence of alternative artefact classifications [15], the specific demarcation amongst signal as well as artifact is typically dictated with the purpose of those collecting the data. Muscle artefacts, 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 artefact in each EEG demo, it's no wonder that artefact identification strategies are solely concerned with removing the intruding artefact [2]. According to one school of thought, an EEG fragment aberration is considered an artefact if it affects or hinders 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 Artefacts

When EEG data is acquired using recording equipment, signal artefacts are more visible. These artefacts can corrupt EEG data. To properly eradicate artefacts or noise in this scenario, a thorough understanding of the various types of artefacts is essential. Noise in the surrounding environment, experimental errors, and physiological artefacts all create unwanted signals known as artefacts. Furthermore, external elements such as the surroundings and experimental error are classed as extrinsic artefacts; physiological artefacts, on the other hand, are categorised as intrinsic artefacts. The examples of intrinsic artefacts include eye blinks, muscle activity, and heartbeats. Figure 1 depicts the three most common physiological artefacts 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.

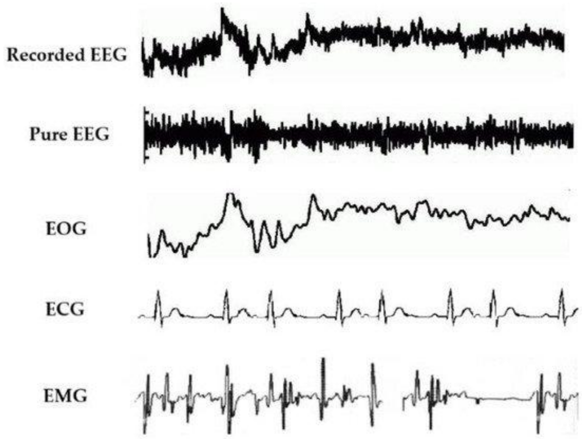

Fig. 1. Types of EEG Artefacts

III. SCOPE OF REVIEW

This research provides techniques for detecting and correcting artefacts 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 artefacts 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 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 Artefact	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

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

3.2. Metrics

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

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Furthermore, many researchers employ future objective execution as a criterion for restitution accuracy; for example, artefact 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 observe that researchers often assess their strategies using information they have gathered themselves rather than a uniform community benchmark dataset; this reflects a greater concern in the EEG research field regarding information exchange procedures. Whenever information is distributed, it is often to investigate a specific downstream goal; as a result, artefacts are frequently removed, rendering the dataset useless for artefact 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 and quantitative methodologies has been utilised in the field of artefact identification. We will go over each of these strategies in more detail below. [15, 16]

4.1. Hand-Crafted Methods

To perceive the signal qualities of eye blink artefacts, the BLINK technique was designed primarily for this purpose. This methodology, like other handcrafted approaches, works effectively for the purpose it was intended to do, but it cannot constantly be improved, adjusted or modified to identify various forms of artefacts [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 into their core signal constituents, allowing an analyst to identify and eliminate artefacts. Despite the existence of several criteria for distinguishing artefacts 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 artefacts 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 supervised classification algorithms that have been used to handle a range of EEG artefact identification challenges. In the realm of EEG artefact identification, deep learning and neural network approaches are relatively new developments. To depict EEG data, a convolutional neural network (CNN) has been utilised as a $p \times q$ representation, with p channels and q samples, in several recent studies. Nejedly et al. used a CNN in conjunction with fully automated image processing techniques to detect artefacts in intra-cerebral EEG data [6]. Deep learning was often employed to improve the efficiency of “network models” created on a range of datasets [5]. Finally, trained systems were proven to differentiate artefacts from frequency sequences accurately [5, 9], but they necessitate tagged artefact information, which is not easily accessible for numerous EEG databases.

4.4. Unsupervised Methods

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

4.5. Hybrid Approaches

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

V. ARTIFACT REMOVAL AND CORRECTION METHODS

Researchers can obtain proper results by identifying and eliminating artefact-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. Current findings have centred on calculating an "artefact-free" adaptation of the afflicted area rather than rejecting it altogether.

5.1. Signal Decomposition Methods

As mentioned earlier, ICA breaks down EEG signals into their fundamental sources, which can then be used to identify distortions in the signals. The above-mentioned detection methods logically lead to the reconstruction of the EEG information, excluding only the additive noise. Gilbert et al. [5] used numerous classifiers (LDA, SVM, KNN) to differentiate among signals in addition to aspects which are noise independent. In contrast, [10] used a CNN classifier to make a distinction among noise plus signal mechanisms, as mentioned earlier. Interestingly, when the signal is regenerated, these approaches sometimes result in temporal data loss [13]. Artefact Subspace Reconstruction (ASR), which essentially examines the statistical features of constituents generated by Principal Component Analysis (PCA), is another method for blind source separation. While both ASR and ICA-based

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techniques are equally successful, the latter is simpler and requires less computer power, making it better suited for online artefact elimination. [11]

EEG artefact 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 belong to the same genre.

EMDs break signals into a specific type of producing feature that optimizes the reconstruction's SNR. Although EMDs look to be like 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 the EEMD process.

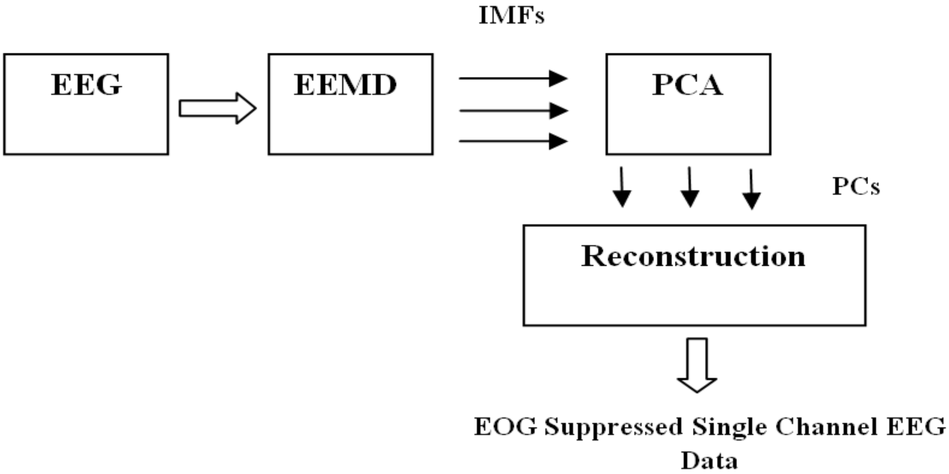

Fig. 2. Block Diagram of Enhanced Empirical Mode Decomposition

5.2. Filter-Based Approach

Filters are fundamental signal processing segment features that reduce unwanted temporal occurrences. Wiener filters anticipate signal and noise propagation characteristics using labelled samples, allowing the noisy amplitude to be filtered out while lowering the NMSE between the pure signal and its estimate. To use MWF, just basic labelling 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 also make this assumption. Neural encoder-decoder models with enough depth can learn to fix a variety of artefacts from various backgrounds. The schematic diagram of MWF is shown in Figure 3.

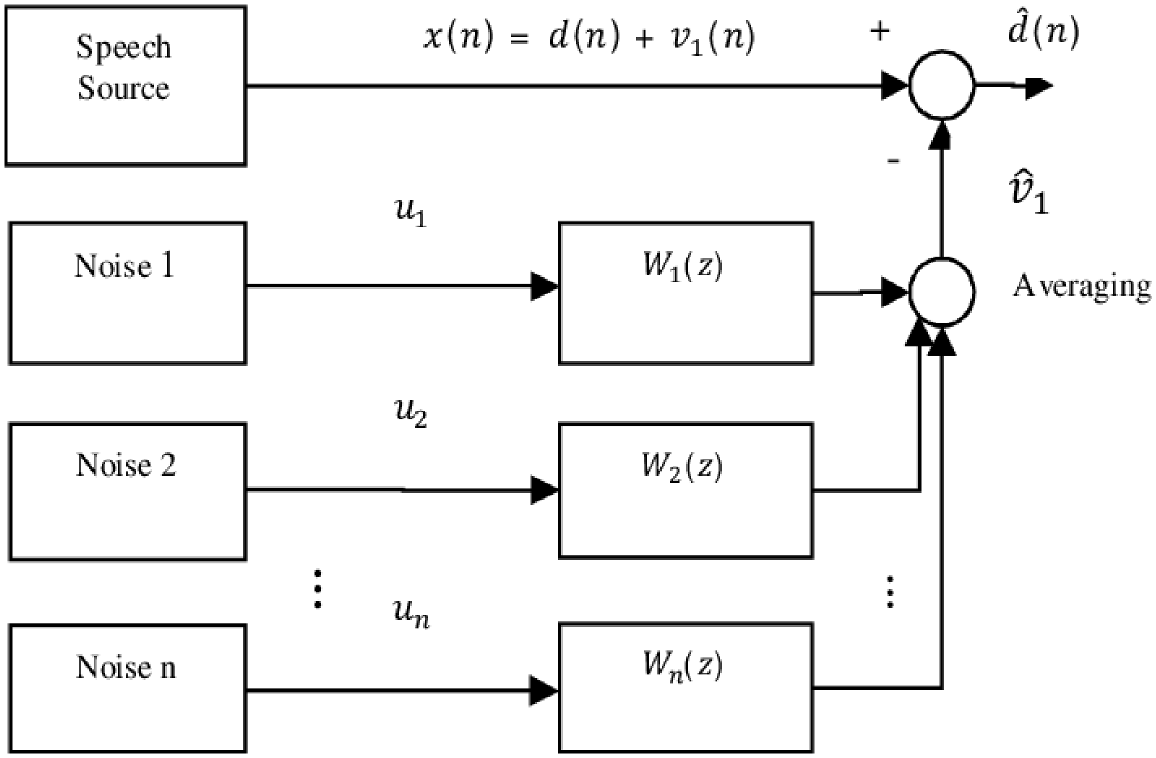

Fig. 3. Block Diagram of Multi-Channel Wiener Filter

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5.3. Supervised Methods

Artefact eradication with neural networks is a relatively novel approach, facilitated by advances in encoder-decoder neural network topologies for sequence-to-sequence modelling problems. Investigators employ noisy samples as the original signal for the encoder-decoder framework and artefact-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 artefacts, was subsequently provided to aid efforts in artefact rectification [13]. The authors' programme enables the modelling of numerous artefacts at different SNR levels. 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 artefact recognition, as previously mentioned. Artefact-free trials were utilised to train a CNN to reconstruct EEG segments using nearby data with high accuracy. The artefact-ridden areas were then recreated using the trained network. The technique ensures that the restored information appears artefact-free by conditioning with "artefact-free" trials. Even though the artefact eradication phase was supervised, the workflow overall did not require labelling due to the unsupervised artefact detection. This method might also be applied to any other supervised artefact elimination feature, such as [7, 9]. The exactness of unsupervised artefact 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 from the reconstruction.

VI. RESULTS AND DISCUSSION

As illustrated in Table 2, the field of EEG artefact identification research is in critical need of a uniform metric, database, and terminology, particularly if the objective is to generate a helpful 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 artefact identification and rectification approaches in this article, with an emphasis on the last five years of investigation. We examined a significantly larger number of publications than those included in this paper. As EEG monitors become more widely used in various sectors, there has been a surge in concern regarding the recognition and elimination of artefacts.

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Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	The present article has been submitted with equal contributions from both authors.

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