EEG Artifact Removal Strategies for BCI Applications: A Survey

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Abstract: This paper aims to provide a comprehensive examination of the Brain-Computer Interface and the more scientific discoveries that have resulted from it. The ultimate goal of this review is to provide extensive research in BCI systems while also focusing on artifact removal techniques or methods that have recently been used in BCI and important aspects of BCIs. In its pre-processing, artifact removal methodologies were critical. Furthermore, the review emphasizes the applicability, practical challenges, and outcomes associated with BCI advancements. This has the potential to accelerate future progress in this field. This critical evaluation examines the current state of BCI technology as well as recent advancements. It also identifies various BCI technology application areas. This detailed study shows that, while progress is being made, significant challenges remain for user advancement A comparison of EEG artifact removal methods in BCI was done, and their usefulness in real-world EEG-BCI applications was talked about. Some directions and suggestions for future research in this area were also made based on the results of the review and the existing artifact removal methods.

Keywords: EEG: Electro Encephalo Gram; BCI: Brain-Computer Interface; ECG: Electrocardiogram;EMG: ElectroMyoGram;EOG: ElectroOculogram

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1. Introduction

Recent advances in biomedical engineering, medicine, and information technology have enabled the development of electroencephalography-based Brain-Computer Interfaces that do not require invasive brain surgery [1,2]. Disproportion in these frequencies is used to diagnose certain disorders and diseases [3,4], and numerous studies of EEG signals have shown that certain signal bands are strongly associated with particular activities. Table 1 shows the various brain wave patterns and activities.

The term "Brain-Computer Interface" (also "Brain-Machine Interface," "Human Computer Interface," or "Neural Interface") refers to the integration of hardware and software to facilitate communication between a biological object and a computer. The fields of neuroscience, signal processing, and clinical research all intersect with AI and ML in BCI studies, making them an interdisciplinary field in and of themselves.

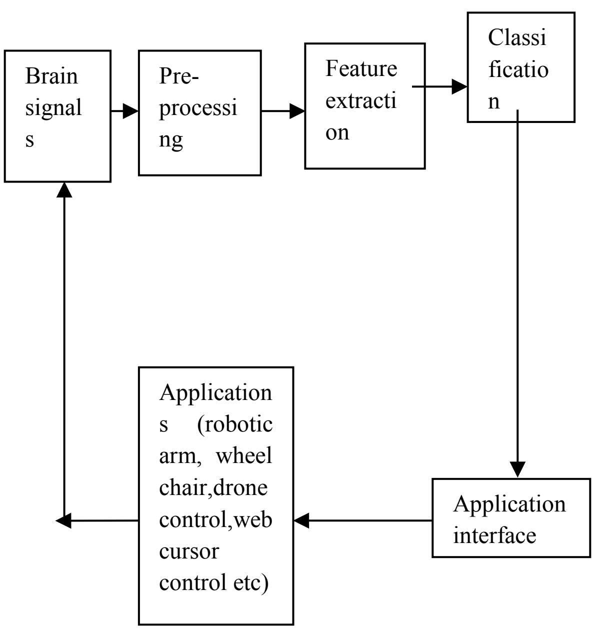
Table.1. Different brain rhythms and their brain activities

Frequency band	**Frequency**	**Brain states**	**Best recorded at**
Gamma (γ)	>40Hz	Concentration	Parietal Lobe,active frontal lobe

Beta (β)	14–40Hz	Awakening,conscious and rational contemplation.	Parietal Lobe,Frontal Lobe
Alpha (α)	9–14Hz	Comfortable,idle,not concentrating on anything	Occipital Lobe,Frontal Lobe
Theta (θ)	4–8 Hz	Dreaming or sleeping and meditation	-------
Delta (δ)	0.3–4 Hz	Sleep,the most profound relaxation and restorative, healing sleep	-----

The BCI system's operation necessitates the use of three modules:

1.signal capturing
2. processing of signals
3. application interface & applications



2. Signal Capturing Block

The electrophysiological signals used by the BCI are captured by the Signal Capturing Module. The brain is the source of these signals [7]. Both invasive and non-invasive methods have been developed for BCI research, but invasive methods like electrocardiograms (ECoG) and single-neuron recordings have proven more effective [7,8]. Comparison of signal quality with other non-invasive brain imaging techniques, including magnetoencephalography, positron emission tomography, functional magnetic resonance imaging, near-infrared spectroscopy, and fMRI [8]. The acquired signals are amplified to increase their strength before transmission. Before any computer application, they must be encoded.

3. Processing Of Signals Block

3.1 Signal Pre-Processing

As illustrated in Figure 2, preprocessing of EEG signals is an essential first step in any brain-computer interface-based application. The signal is cleaned up by subtracting out artifacts like ECG, EOG, and EMG measurements, filtering out noise, and resampling it to meet detector input specifications.

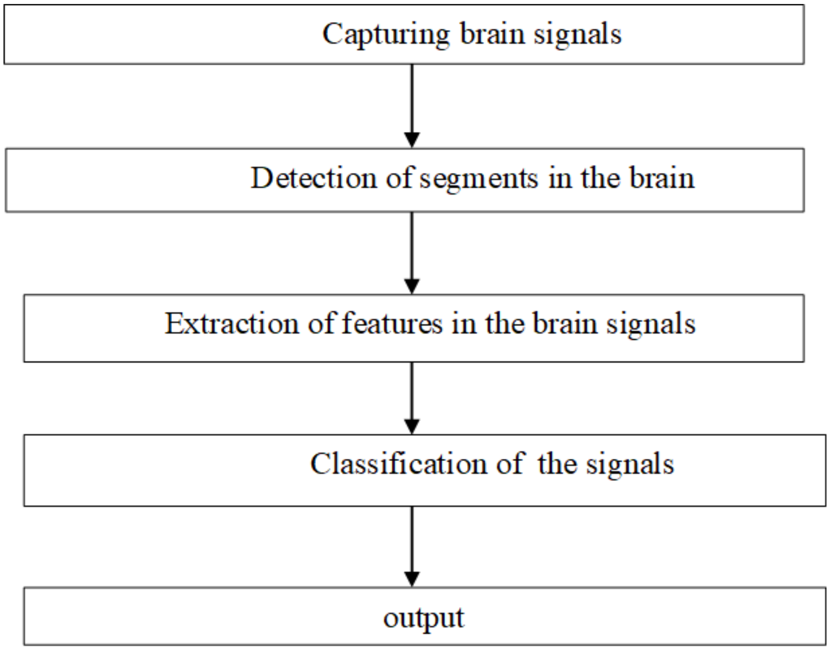


Fig.2.Signal preprocessing steps in BCI system

Pre-processing is often done to increase the recorded data's signal to noise ratio before processing. Artifacts in the EEG signal can be eliminated by filtering out the electrical activity produced by head and eye muscle contractions. In order to remove artifacts from an EEG recording, a preprocessing of the signal is required. When properly implemented, BCI systems can Accurate categorization relies heavily on the EEG signal being properly preprocessed. The EEG signal can be cleaned up and made ready for analysis by doing some preliminary processing. BSS, which stands for "blind source separation," is a popular pre-processing method [9].Artifacts are frequently observed in many forms of EEG signals, as shown in Table 2.

Table.2.Different artifacts arised during signal acquisition of EEG signal processing

S.No	Artifacts	Generated By The Source	Frequency	Voltage Level	Shape /Structure
1	Ocular Artifacts (EOG)	Eye	0.3 -3HZ	80-100mv	Delta waves
2	EMG	Jaw movements	4-6hz	0-10mv	Theta waves
3	ECG	Heart or cardiac movement	0-150hz	1-10mv	Beta and gamma waves
4	50/60 HZ artifacts(power line artifacts)	Power line attached	50/60 hz	high	Beta and gamma waves
5	Sweat artifacts	sweat	0.25-0.5 hz	300 micro volts	Delta waves
6	Electrode pop	Electrodes attached to scalp	0-30hz	20 mv	Shape appeared different from actual EEG signal

7	Physical movement artifacts(motion artifacts)	Body movements,head movement,jaw movement etc…	Very low	high	Shape appeared different from actual EEG signal
8	Electronic gadgets artifacts	Mobile,laptop,personal computer etc..	Very low	high	Shape appeared different from actual EEG signal

4. Literature Survey

The below table.3 compare the latest artifacts removal techniques in various parameters such as type of artifacts that can able to eliminate in EEG signal processing which is mainly related to BCI applications ,novelty in the algorithm or method that chosen to mitigate artifacts ,the data that can operated on which the proposed method can best suited (real &simulated) so that we can estimate practical implementation, and also here discussed the challenges or limitations faced to practical viability and commented or given remarks about each and every system of implementation. The above table contain different artifacts removal techniques EOG, ECG, EMG, Physical movement artifacts(motion artifacts) etc but mainly focused on ocular or Eye Blink (EB) artifacts because the EB artifacts are main cause of error or distortion in EEG signal pre-processing.

Table 3. Comparison of various artifacts removal techniques

Author	Type of artifact	Method	Algorithm used	Novelty	Data	Challenges/ limitations	Comments
Çınar, Salim(2021)[22]	Only Eye blink (EOG)	Independent Component Analysis (ICA), Kurtosis, K-means, Modified Z-Score (MZS) and Adaptive Noise Canceller (ANC).	The classical Least Mean Squares (LMS) and Normalized LMS (NLMS) algorithms	The proposed system does require an external electrode for measuring EOG Signals	Real &simulated	It is only applicable to this method is that ocular artifacts and other artifacts present it is not efficient method and When conducting the subtraction process, the disadvantage is the relevant EEG signals can be erased.	The proposed method has high performance in both datasets & comfortable measurement for patients during more time EEG recordings.
Cao, Jiuwen.et al. (2021) [24]	Only Eye	Gaussian mixture	cascaded hybrid thresholdin	No false positives were found	Real and simulated	An increased likelihood	In terms of precision

	blink (EOG	model (GMM)	g method and the GMM algorithm	in the detection of eye blink artifacts using the suggested approach.		of missing artifacts caused by eye blinks when employing a high threshold.	and F1 score, the proposed approach is more reliable.
Egambaram, Ashvaany.et al. [26]	Only Eye blink (EOG	FastEMD-CCA and FastCCA	It is proposed to use a combination of modified Empirical Mode Decomposition and Canonical Correlation Analysis to perform unsupervised eye blink artifact detection (eADA).	More than 97% Removal Accuracy and an average of 10-13ms removal speed	simulated	The artifact-free EEG samples showed negligible variation.	Eyeblink artifacts can be effectively removed online with minimal neural distortion.
Borowicz, Adam. [27]	Only Eye blink (EOG	independent component analysis (ICA) and principles of regression analysis	multichannel Wiener filter (MWF) and a small subset of the frontal electrodes	When compared to the ICA approach, the suggested algorithm is more straightforward. Real-time systems can benefit more from it, and that seems to be a crucial factor in BCI research and	Real and simulated	utilizing cutting-edge multichannel linear filters, enhanced off-line implementation, and expanding the suggested method's applicability to additional types of biomedical data.	When compared to the state-of-the-art method, the new methodology is more suitable to real-time systems.

				developme nt.			
Zhou, Weidong, and Jean Gotman [28]	Only Eye blink (EOG	ICA method	Independe nt Componen t Analysis (ICA) combining the EEG di pole model	The ICA algorithm uses few computatio nal resources. Without requiring access to a database of reference artifacts, it can separate the EEG from the noise.	Real and simulate d	The frequency distribution s of slow waves and visual artifacts are very similar.	This method was validated for its ability to automatic ally filter out EEG aberration s attributabl e to the eyes.
. Sreeja, S. R., et al [29]	Mainly Eye blink (EOG) & also used for other artifacts remova l	morpholo gical componen t analysis (MCA) and K-SVD	MCA and K-SVD are two sparsity-based approaches that can be used to eliminate artifacts.	The suggested sparsity-based approaches can eliminate EB artifacts in an EEG signal without the use of any specialized equipment or additional channels for the EOG.	Real and simulate d	One major drawback is that it necessitates the use of extraocular channels in order to capture ocular artifacts.	It is applicable to the eliminatio n of other artifacts in raw EEG data as well.
He, Ping, G. Wilson, and C. Russell [30]	ocular artifacts	adaptive filtering	recursive least squares algorithm	The non-stationary component of EOG signals is monitored using this technique.	real	The approach does not scale up to situations with four or more reference inputs.	automatic ally adjust to a new environm ent without sacrificing performan ce

. Chintala, Sridhar, and Jaisingh Thangaraj[32]	ocular artifacts	Robust Variable Forgetting Factor (RVFF) and Recursive Least Square (RLS)	RVFF-RLS based algorithm	The non-stationary EOG signals are followed and estimated by the algorithm, and then the subtraction approach is used to acquire clean EEG data.	Real and simulated	Non-stationary conditions are detrimental to tracking performance.	The proposed method exhibits the lowest possible mean square error in a time-varying condition.
Yadav, Anchal, and Mahipal Singh Choudhry. [33]	ocular artifacts	EEMD & SCICA Kurtosis and mMSE	Ensemble Empirical Mode Decomposition (EEMD) and Spatial Constraint Independent Component Analysis (SCICA)	To counter act EMD's mode mixing and aliasing, EEMD is employed.	Real	EEMD's amplitude-reduction problem	Better constraints on ICA and wavelet augmented independent component analysis can boost performance even further.
Gajbhiye, Pranjali, Rajesh Kumar Tripathy [34]	ocular artifacts	the FBSE-EWT based rhythm separation technique	. The Fourier-Bessel series expansion based empirical wavelet transform (FBSEEWT	The approach can remove ocular artifact from an EEG recording without the use of a reference signal.	Real	The blending of modes as various rhythmic EEG data appears	Compared to existing methods, the proposed approach improves performance while requiring fewer resources. When compared to other methods, alpha

							wave's MAE in PSD value was 0.029 on average.
Islam, Md Kafiul, Parviz Ghorbanzadeh, and Amir Rastegarnia. [35]	All type of artifacts removal(ECG, EOG, EMG, etc.)	Entropy, kurtosis, skewness, periodic waveform index	stationary wavelet transform based artifact removal	The outcomes demonstrate that the suggested reduction of artifacts significantly increases BCI output.	Real & simulated	The proposed method still requires work in terms of its discrimination abilities and its capacity to eliminate artifacts.	The proposed approach utilizes four statistical techniques to plot the improbability of various artifacts.
Lee, Young-Eun, No-Sang Kwak, and Seong-Whan Lee [36]	Movement artifacts	ICA with online learning	constrained independent component analysis with online learning (cIOL)	Examining the impact of noise reduction in the temporal and frequency domains through a quantitative evaluation of artifact removal approaches utilizing two BCI paradigms (ERP and SSVEP).	Real & simulated	Timeframes for using the approach are constrained by the occurrence of gait events. Another issue is that there isn't a single adequate template to represent artifacts' wide variety.	Developed a rough estimate of the movement artifacts using the EEG data. Finally, artifact-free EEG signals were recovered using weights that were updated using online learning.
Song, YoungJae, and Francisco Sepulveda [37]	EMG artifacts	ICA, PCA, and BSS-CCA	EMG-CCh	Reduce ambiguity and enhance discriminati	simulated	Methodological Constraints An excessive amount of	Finally, the proposed strategy improved class

				on between classes.		class-dependent EMG can persist even in a channel with reduced CRC during resting conditions.	separation (when compared to prior methods) using both training and test data. The data set developed for the BCI competition is used in a wide variety of applications. This strategy can be used independently or in tandem with other approaches of managing artifacts.

According to the data in the table above, the most common techniques used to clean up EEG signals include Blind Source Separation (BSS), Principal Component Analysis (PCA), Canonical Correlation Analysis (CCA), Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD), Wavelet Transform, and Adaptive Filtering. The performance parameters, including the correlation co-efficient, Mean Square Error, Power Spectral Density, Signal-to-Noise Ratio, and Execution Speed and Complexity, are all improved when the preprocessing stage is enhanced.

The above table details a discussion of advanced artifact removal techniques for the examples given, including those by nar, Salim(2021), who discussed and implemented a new algorithm, the classical Least Mean Squares (LMS) algorithm, and the Normalized LMS algorithm (using Independent Component Analysis, Kurtosis, K-means, a modified Z-score, and an adaptive noise canceler) for removing eye blink artifacts from both real and simulated data. The system has the limitation of only being able to deal with ocular artifacts, making it a less-than-efficient method; the subtraction process can result in the loss of important EEG signals; and in another paper by Borowicz and Adam, they discussed independent component analysis (ICA) and regression analysis principles and implemented them using a multichannel Wiener filter; and in this study, they used a subset of frontal electrodes to detect ICA. It also works great with real-time systems, which is apparently crucial for BCI research. Additionally, a novel concept was implemented by Zhou, Weidong, and Jean Gotman using Independent Component Analysis in combination with the EEG dipole model, with a primary focus on ocular artifact elimination. This technique was found to be effective in automatically eradicating ocular artifacts from the EEG. Song, YoungJae, and Francisco Sepulveda also implemented the system using ICA, in addition to PCA, and BSS-CCA to remove EMG artifacts by a novel technique called EMG-cch and best suited for use along with the other techniques the data only implemented on simulation results.

Genetic algorithm (GA), a technique proposed by Trigui, Omar, et al., decreases the RMSE between unprocessed and processed EEG data. Using only simulated data and a small number of channels, the proposed approach nevertheless achieves satisfactory results.

Each and every eye blink artifact was correctly identified by the proposed method by Cao, Jiuwen.etal, with zero false positives.

The method developed by Egambaram, Ashvaany, et al. CFast EMD-CCA and Fast CCA introduced a method for detecting eye blink artifacts without human supervision by combining a variant of Empirical Mode Decomposition with Canonical Correlation Analysis. Artifact-free EEG segments showed hardly any distortion, with an accuracy of more than 97% and a removal speed of 10-13 ms, on average. Artifacts caused by an eyeblink can be corrected online with minimal neural distortion.

To eliminate EB artifacts from the EEG signal, Sreeja, S. R., et al. suggested a method known as K-SVD with morphological component analysis. Both of these methods are sparsity-based methodologies that work on both real and simulated data without the need for channel information, parameter tweaking (such as thresholding), or additional hardware/EEG channels.

Adaptive filtering for ocular artifacts using recursive least squares was given by He, Ping, G. Wilson, and C. Russell. When applied to real-world data, this method follows the dynamic components of EOG signals. It cannot be generalized to situations involving three or more reference inputs, but it can be automatically adapted to a new setting without compromising its efficacy.

Using the Robust Variable Forgetting Factor (RVFF) and Recursive Least Square (RLS), Chintala, Sridhar, and Jaisingh Thangaraj solved the problem of ocular artifacts. This method estimates and follows non-stationary EOG signals so that pure EEG signals can be extracted from both real and simulated data. In unstable conditions, tracking accuracy decreases. The proposed method achieves the smallest mean square error in a dynamic environment.

Yadav, Anchal, and Mahipal Singh Choudhry compute Kurtosis and mean squared error (mSSE) using Ensemble Empirical Mode Decomposition (EEMD) and Spatial Constraint Independent Component Analysis (SCICA). EEMD is also used to overcome the mode mixing and aliasing problem of EMD, which is typically performed on Real data. Improving the constraints used in ICA and wavelet-enhanced independent component analysis can further boost performance. In order to get rid of ocular artifacts, Gajbhiye, Pranjali, and Rajesh Kumar Tripathy presented a rhythm separation technique based on FBSE-EWT. Ocular artifacts can be removed from an EEG signal using the Fourier-Bessel series expansion based empirical wavelet transform (FBSEEWT) method, which has been extensively validated for real-valued data and does not require a reference signal. When many modes of EEG rhythm information appear, this phenomenon is referred to as "mode mixing." The suggested method outperforms state-of-the-art alternatives, with a mean absolute error (MAE) in peak signal-to-noise ratio (PSR) of only 0.029 for rhythm.

Using entropy, kurtosis, skewness, and the stationary wavelet transform, Islam, Md. Kafiul, Parviz Ghorbanzadeh, and Amir Rastegarnia proposed a method for eliminating artifacts across all modalities. When evaluated with real and simulated data, the results reveal that the proposed artefact removal significantly improves BCI output. The proposed technique still needs better discrimination capacity and has weak ability to eliminate genuine artefacts. The suggested method for mapping artificial probability uses four statistical parameters.

5. Conclusion

The work is mostly considered in the preprocessing step of the overall BCI systems. The goal of the pre-processing stage in a BCI applications is to decrease artifacts in the EEG signal generated by the numerous sources. Based on the findings in the available literature, this report summarized the key techniques, Some of the techniques uses exclusively used for removing artifacts which is related to eye blink (EOG)artifacts, ECG ,EMG and all other movement related artifacts here by go through the different research articles basically uses different algorithams separately or combinely that reveals the output without artifacts in EEG signal processing which combined with BCI related applications either it may be cursor movement,wheel chair movement,video gaming,bio medical etc. Some methods, such as adaptive filtering, Morphological Component Analysis (MCA) and K-SVD and Entropy, kurtosis, skewness, periodic waveform index, remove artifacts with high precision,which works on both real and simulated data or either of the one , however methods with high computational cost may not be suited for online applications. As a result, there is no best option for removing all forms of artifacts. So, one of the future goals of effective artifact attenuation is to provide an application-specific methodology with improved time and precision, efficiency.

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