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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, BCI, ECG, EMG, EOG.

1. INTRODUCTION

1.1. 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.

1.2. Signal Capturing Block

As illustrated in Fig. 1, 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.

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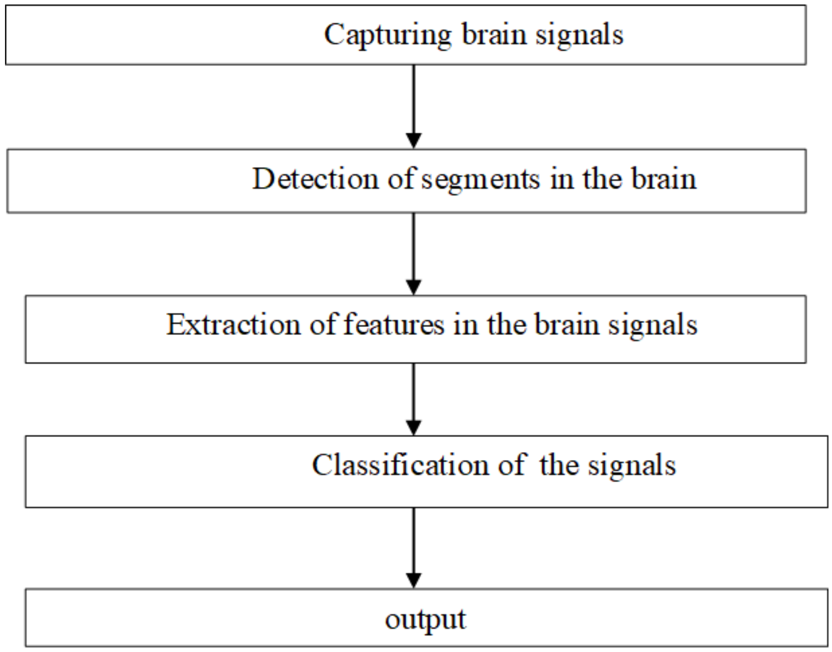

Fig. 1. Stage of the Signal Processing in BCI.

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 1.

Table 1. 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

2. LITERATURE REVIEW

The below Table.2 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 2. 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 blink (EOG	Gaussian mixture model (GMM)	cascaded hybrid thresholding method and the GMM algorithm	No false positives were found in the detection of eye blink artifacts using the suggested approach.	Real and simulated	An increased likelihood of missing artifacts caused by eye blinks when employing a high threshold.	In terms of precision and F1 score, the proposed approach is more reliable.
Egambaram, Ashvaany.etal. [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 development.	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.
Zhou, Weidong, and Jean Gotman [28]	Only Eye blink (EOG	ICA method	Independent Component Analysis (ICA) combining the EEG dipole model	The ICA algorithm uses few computational resources. Without requiring access to a database of reference artifacts, it can separate the EEG from the noise.	Real and simulated	The frequency distributions of slow waves and visual artifacts are very similar.	This method was validated for its ability to automatically filter out EEG aberrations attributable to the eyes.
. Sreeja, S. R., et al [29]	Mainly Eye blink (EOG) & also used for other artifacts removal	morphological component 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 simulated	One major drawback is that it necessitates the use of extraocular channels in order to capture ocular artifacts.	It is applicable to the elimination 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.	automatically adjust to a new environment without sacrificing performance

. 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 discrimination between classes.	simulated	Methodological Constraints An excessive amount of class-dependent EMG can persist even in a channel with reduced CRC during resting conditions.	Finally, the proposed strategy improved class 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.

3. 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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Ethics. The authors declare that the present research work has fulfilled all relevant ethical guidelines required by COPE.

REFERENCES

[1] Kübler, A. (2020). The history of BCI: From a vision for the future to real support for personhood in people with locked-in syndrome. *Neuroethics*, *13*(2), 163-180.
[2] Kawala-Janik, A. Efficiency Evaluation of External Environments Control Using Bio-Signals. Ph.D. Thesis, University of Greenwich, London, UK, 2013.
[3] Ebersole, J.S.; Pedley, T.A. Current Practice of Clinical Electroencephalography; Lippincott Williams & Wilkins: Philadelphia, PA, USA, 2003
[4] Millett, D. Hans Berger: From psychic energy to the EEG. Perspect. Biol. Med. 2001, 44, 522–542. [CrossRef] Priyanka A. Abhang, Bharti W. Gawali, Suresh C. Mehrotra,
[5] Chapter 2 - Technological Basics of EEG Recording and Operation of Apparatus,Editor(s): Priyanka A. Abhang, Bharti W. Gawali, Suresh C. Mehrotra,Introduction to EEG- and Speech-Based Emotion Recognition,Academic Press,2016
[6] Aggarwal, Swati, and Nupur Chugh. **"Signal processing techniques for motor imagery brain computer interface: A review."** *Array* 1 (2019): 100003.
[7] Donoghue JP. Connecting cortex to machines: recent advances in brain interfaces. Nat Neurosci 2002;5:1085.
[8] 8.Serruya Mijail D, et al. Brain-machine interface: instant neural control of a movement signal. Nature 2002;416:141.
[9] Cichocki, Andrzej, et al. **"EEG filtering based on blind source separation (BSS) for early detection of Alzheimer's disease."** *Clinical Neurophysiology* 116.3 (2005): 729-737.
[10] Al-Fahoum, Amjed S., and Ausilah A. Al-Fraihat. **"Methods of EEG signal features extraction using linear analysis in frequency and time-frequency domains."** *International Scholarly Research Notices* 2014 (2014).
[11] Osalusi, Bamidele, Amole Abraham, and David Aborisade. **"EEG Classification in Brain Computer Interface (BCI): A Pragmatic Appraisal."** *American Journal of Biomedical Engineering* 8.1 (2018): 1-11.
[12] Mridha, M. F., et al. "**Brain-computer interface: Advancement and challenges."** *Sensors* 21.17 (2021): 5746.
[13]] Phan A H and Cichocki A 2010 Tensor decompositions for feature extraction and classification of high dimensional datasets Nonlinear Theory Appl. 1 37–68
[14] Washizawa Y, Higashi H, Rutkowski T, Tanaka T and Cichocki A 2010 Tensor based simultaneous feature extraction and sample weighting for EEG classification Int. Conf. on Neural Information Processing, ICONIP 2010: Neural Information Processing. Models and Applications (Berlin: Springer) pp 26–33
[15] Onishi A, Phan A, Matsuoka K and Cichocki A 2012 Tensor classification for P300-based brain computer interface IEEE Int. Conf. on Acoustics, Speech and Signal Processing (IEEE) pp 581–4
[16] Zhang Y, Zhou G, Jin J, Wang X and Cichocki A 2014**, "Frequency recognition in SSVEP-based BCI using multiset canonical correlation analysis"**. *Int. J. Neural Syst*. 24 1450013
[17] Zhang Y, Zhou G, Jin J, Wang X and Cichocki A 2015 Optimizing spatial patterns with sparse filter bands for motor-imagery based brain–computer interface J. Neurosci. Methods 255 85–91

[18] Zhang, Y. U., Zhou, G., Jin, J., Wang, X., & Cichocki, A. (2014). **“Frequency recognition in SSVEP-based BCI using multiset canonical correlation analysis”.** *International journal of neural systems*, *24*(04), 1450013.

[19] Zhang, Y., Zhou, G., Jin, J., Wang, X., & Cichocki, A. (2015). “**Optimizing spatial patterns with sparse filter bands for motor-imagery based brain–computer interface”.** *Journal of neuroscience methods*, *255*, 85-91.

[20] Zhang, Y., Zhou, G., Jin, J., Zhang, Y., Wang, X., & Cichocki, A. (2017). **“Sparse Bayesian multiway canonical correlation analysis for EEG pattern recognition”**. *Neurocomputing*, *225*, 103-110.

[21] Zhang Y, Zhou G, Zhao Q, Onishi A, Jin J, Wang Xand Cichocki, 2011, **“Multiway canonical correlationanalysis for frequency components recognition in SSVEP-based BCIs”**, *Neural Information Processing*(Berlin: Springer)

[22] Çınar, Salim. "**Design of an automatic hybrid system for removal of eye-blink artifacts from EEG recordings."** *Biomedical Signal Processing and Control* 67 (2021): 102543.

[23] Trigui, Omar, et al. **"Removal of eye blink artifacts from EEG signal using morphological modeling and orthogonal projection."** *Signal, Image and Video Processing* 16.1 (2022): 19-27.

[24] Cao, Jiuwen, et al. **"Unsupervised eye blink artifact detection from EEG with Gaussian mixture model."** *IEEE Journal of Biomedical and Health Informatics* 25.8 (2021): 2895-2905.

[25] Wang, Jianhui, et al. **"Eye blink artifact detection with novel optimized multi-dimensional electroencephalogram features."** *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 29 (2021): 1494-1503.

[26] Egambaram, Ashvaany, et al**. "Online detection and removal of eye blink artifacts from electroencephalogram."** *Biomedical Signal Processing and Control* 69 (2021): 102887.

[27] Borowicz, Adam. **"Using a multichannel Wiener filter to remove eye-blink artifacts from EEG data."** *Biomedical Signal Processing and Control* 45 (2018): 246-255.

[28] Zhou, Weidong, and Jean Gotman. "**Automatic removal of eye movement artifacts from the EEG using ICA and the dipole model."** *Progress in Natural Science* 19.9 (2009): 1165-1170.

[29] Sreeja, S. R., et al. **"Removal of eye blink artifacts from EEG signals using sparsity."** *IEEE journal of biomedical and health informatics* 22.5 (2017): 1362-1372.

[30] He, Ping, G. Wilson, and C. Russell. **"Removal of ocular artifacts from electro-encephalogram by adaptive filtering."** *Medical and biological engineering and computing* 42.3 (2004): 407-412.

[31] Joyce, Carrie A., Irina F. Gorodnitsky, and Marta Kutas. **"Automatic removal of eye movement and blink artifacts from EEG data using blind component separation."** *Psychophysiology* 41.2 (2004): 313-325.

[32] Chintala, Sridhar, and Jaisingh Thangaraj. **"Ocular artifact elimination from eeg signals using rvff-rls adaptive algorithm."** *2020 National Conference on Communications (NCC)*. IEEE, 2020.

[33] Yadav, Anchal, and Mahipal Singh Choudhry. **"A new approach for ocular artifact removal from EEG signal using EEMD and SCICA.**" *Cogent Engineering* 7.1 (2020): 1835146.

[34] Gajbhiye, Pranjali, Rajesh Kumar Tripathy, and Ram Bilas Pachori. **"Elimination of ocular artifacts from single channel EEG signals using FBSE-EWT based rhythms."** *IEEE Sensors Journal* 20.7 (2019): 3687-3696.

[35] Islam, Md Kafiul, Parviz Ghorbanzadeh, and Amir Rastegarnia. **"Probability mapping based artifact detection and removal from single-channel EEG signals for brain–computer interface applications."** *Journal of Neuroscience Methods* 360 (2021): 109249.

[36] Lee, Young-Eun, No-Sang Kwak, and Seong-Whan Lee. **"A real-time movement artifact removal method for ambulatory brain-computer interfaces."** *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28.12 (2020): 2660-2670.

[37] Song, Y., & Sepulveda, F. (2018). **“A novel technique for selecting EMG-contaminated EEG channels in self-paced brain–computer Interface task onset”.** *IEEE Transactions on neural systems and rehabilitation engineering*, *26*(7), 1353-1362.

[38] Krauledat, Matthias, et al. "**Robustifying EEG data analysis by removing outliers."** Chaos and Complexity Letters 2.3 (2007): 259-274. J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[39] Gouy-Pailler, Cédric, et al. **"Iterative subspace decomposition for ocular artifact removal from EEG recordings."** *International Conference on Independent Component Analysis and Signal Separation. Springer*, Berlin, Heidelberg, 2009. K. Elissa, **“Title of paper if known,”** unpublished.

[40] Croft, Rodney J., et al. **"EOG correction: a comparison of four methods."** Psychophysiology 42.1 (2005): 16-24. Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, **“Electron spectroscopy studies on magneto-optical media and plastic substrate interface,”** IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

[41] M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[42] Jiang, Aimin, et al. **"Efficient CSP algorithm with spatio-temporal filtering for motor imagery classification."** IEEE *Transactions on Neural Systems and Rehabilitation Engineering* 28.4 (2020): 1006-1016.

[43] Isa, NE Md, et al. **"Motor imagery classification in Brain computer interface (BCI) based on EEG signal by using machine learning technique."** *Bulletin of Electrical Engineering and Informatics* 8.1 (2019): 269-275.

[44] Ang, Kai Keng, et al. **"Filter bank common spatial pattern (FBCSP) in brain-computer interface."** *2008 IEEE international joint conference on neural networks (IEEE world congress on computational intelligence)*. IEEE, 2008.

[45] Ramoser, Herbert, Johannes Muller-Gerking, and Gert Pfurtscheller. **"Optimal spatial filtering of single trial EEG during imagined hand movement."** *IEEE transactions on rehabilitation engineering* 8.4 (2000): 441-446.

[46] Oh, Seung-Hyeon, Yu-Ri Lee, and Hyoung-Nam Kim. "**A novel EEG feature extraction method using Hjorth parameter.**" *International Journal of Electronics and Electrical Engineering* 2.2 (2014): 106-110.

[47] Übeyli, Elif Derya, and İnan Güler. **"Features extracted by eigenvector methods for detecting variability of EEG signals."** *Pattern Recognition Letters* 28.5 (2007): 592-603.

[48] Stancin, Igor, Mario Cifrek, and Alan Jovic. **"A review of EEG signal features and their application in driver drowsiness detection systems."** *Sensors* 21.11 (2021): 3786.

[49] Stam, CJ van, and E. C. W. Van Straaten. **"The organization of physiological brain networks."** *Clinical neurophysiology* 123.6 (2012): 1067-1087.

[50] Übeyli, Elif Derya. **"Analysis of EEG signals by implementing eigenvector methods/recurrent neural networks.**" *Digital Signal Processing* 19.1 (2009): 134-143.

[51] Gaur, Pramod, et al. **"A sliding window common spatial pattern for enhancing motor imagery classification in EEG-BCI."** *IEEE Transactions on Instrumentation and Measurement* 70 (2021): 1-9.

[52] Bose, Rohit, et al. "**Performance analysis of left and right lower limb movement classification from EEG.**" *2016 3rd International Conference on Signal Processing and Integrated Networks (SPIN)*. IEEE, 2016.

[53] Raschka, Sebastian, David Julian, and John Hearty. Python: deeper insights into machine learning. Packt Publishing Ltd, 2016.

[54] Isa, NE Md, et al. **"Motor imagery classification in Brain computer interface (BCI) based on EEG signal by using machine learning technique."** *Bulletin of Electrical Engineering and Informatics* 8.1 (2019): 269-275.

[55] Rish, Irina. **"An empirical study of the naive Bayes classifier."** *IJCAI 2001 workshop on empirical methods in artificial intelligence*. Vol. 3. No. 22. 2001.

[56] Leung, K. Ming. **"Naive bayesian classifier."** *Polytechnic University Department of Computer Science/Finance and Risk Engineering* 2007 (2007): 123-156.

[57] Berrar, Daniel. **"Cross-Validation."** (2019): 542-545.

[58] Ang, Kai Keng, et al. **"Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b."** *Frontiers in neuroscience* 6 (2012): 39.

[59] Shenoy, H. Vikram, A. Prasad Vinod, and Cuntai Guan. "**Shrinkage estimator based regularization for EEG motor imagery classification.**" 2015 10th International Conference on Information, Communications and Signal Processing (ICICS). IEEE, 2015.

[60] Lupu, R. G., Ungureanu, F., & Cimpanu, C. (2019, May). **"Brain-computer interface: Challenges and research perspectives".** In *2019 22nd International Conference on Control Systems and Computer Science (CSCS)* (pp. 387-394). IEEE.

[61] Fouad, M. M., Amin, K. M., El-Bendary, N., & Hassanien, A. E. (2015). **"Brain computer interface: a review".** *Brain-computer interfaces*, 3-30.

[62] Urigüen, J. A., & Garcia-Zapirain, B. (2015). "**EEG artifact removal—state-of-the-art and guidelines".** *Journal of neural engineering*, *12*(3), 031001.

[63] Islam, M. K., Rastegarnia, A., & Yang, Z. (2016). **"Methods for artifact detection and removal from scalp EEG: A review".** *Neurophysiologie Clinique/Clinical Neurophysiology*, *46*(4-5), 287-305.

[64] Mumtaz, W., Rasheed, S., & Irfan, A. (2021**). "Review of challenges associated with the EEG artifact removal methods".** *Biomedical Signal Processing and Control*, *68*, 102741.

[65] Radüntz, T., Scouten, J., Hochmuth, O., & Meffert, B. (2015**). "EEG artifact elimination by extraction of ICA-component features using image processing algorithms".** *Journal of neuroscience methods*, *243*, 84-93.

[66] Radüntz, T., Scouten, J., Hochmuth, O., & Meffert, B. (2017). **"Automated EEG artifact elimination by applying machine learning algorithms to ICA-based features".** *Journal of neural engineering*, *14*(4), 046004.

[67] Roy, V., Shukla, P. K., Gupta, A. K., Goel, V., Shukla, P. K., & Shukla, S. (2021). **"Taxonomy on EEG artifacts removal methods, issues, and healthcare applications".** *Journal of Organizational and End User Computing (JOEUC)*, *33*(1), 19-46.

[68] Mannan, M. M. N., Kamran, M. A., & Jeong, M. Y. (2018). **"Identification and removal of physiological artifacts from electroencephalogram signals: A review".** *Ieee Access*, *6*, 30630-30652.

[69] Gevins, A. S., Yeager, C. L., Zeitlin, G. M., Ancoli, S., & Dedon, M. F. (1977). **"On-line computer rejection of EEG artifact".** *Electroencephalography and clinical Neurophysiology*, *42*(2), 267-274.

[70] Park, H. J., Jeong, D. U., & Park, K. S. (2002). **"Automated detection and elimination of periodic ECG artifacts in EEG using the energy interval histogram method"**. *IEEE transactions on Biomedical Engineering*, *49*(12), 1526-1533.

[71] Nolan, H., Whelan, R., & Reilly, R. B. (2010). "**FASTER: fully automated statistical thresholding for EEG artifact rejection"**. *Journal of neuroscience methods*, *192*(1), 152-162.

[72] Tatum, W. O., Dworetzky, B. A., & Schomer, D. L. (2011). **"Artifact and recording concepts in EEG".** *Journal of clinical neurophysiology*, *28*(3), 252-263.

[73] Jung, C. Y., & Saikiran, S. S. (2016). **"A review on EEG artifacts and its different removal technique".** *Asia-pacific Journal of Convergent Research Interchange*, *2*(4), 43-60.

[74] Jiang, X., Bian, G. B., & Tian, Z. (2019). **"Removal of artifacts from EEG signals: a review".** *Sensors*, *19*(5), 987.

[75] Roháľová, M., Sykacek, P., Koskaand, M., & Dorffner, G. (2001). **"Detection of the EEG Artifacts by the Means of the (Extended) Kalman Filter".** *Meas. Sci. Rev*, *1*(1), 59-62.

[76] Blum, S., Jacobsen, N. S., Bleichner, M. G., & Debener, S. (2019). **"A Riemannian modification of artifact subspace reconstruction for EEG artifact handling".** *Frontiers in human neuroscience*, *13*, 141.

[77] Shao, S. Y., Shen, K. Q., Ong, C. J., & Wilder-Smith, E. P. (2008). **"Automatic EEG artifact removal: a weighted support vector machine approach with error correction".** *IEEE Transactions on Biomedical Engineering*, *56*(2), 336-344.

[78] Nejedly, P., Cimbalnik, J., Klimes, P., Plesinger, F., Halamek, J., Kremen, V., ... & Jurak, P. (2019). **"Intracerebral EEG artifact identification using convolutional neural networks".** *Neuroinformatics*, *17*(2), 225-234.

[79] Somers, B., Francart, T., & Bertrand, A. (2018). **"A generic EEG artifact removal algorithm based on the multi-channel Wiener filter"**. *Journal of neural engineering*, *15*(3), 036007.

[80] Saba-Sadiya, S., Chantland, E., Alhanai, T., Liu, T., & Ghassemi, M. M. (2021). **"Unsupervised EEG artifact detection and correction"**. *Frontiers in digital health*, *2*, 608920.

[81] Islam, M. K., Rastegarnia, A., & Yang, Z. (2016). **"Methods for artifact detection and removal from scalp EEG: A review".** *Neurophysiologie Clinique/Clinical Neurophysiology*, *46*(4-5), 287-305.

[82] Abreu, R., Leal, A., & Figueiredo, P. (2018). **"EEG-informed fMRI: a review of data analysis methods**". *Frontiers in human neuroscience*, *12*, 29.

[83] Varone, G., Hussain, Z., Sheikh, Z., Howard, A., Boulila, W., Mahmud, M., ... & Hussain, A. (2021). **"Real-time artifacts reduction during TMS-EEG co-registration: a comprehensive review on technologies and procedures".** *Sensors*, *21*(2), 637.

[84] Jung, T. P., Humphries, C., Lee, T. W., Makeig, S., McKeown, M. J., Iragui, V., & Sejnowski, T. J. (1998, September). **"Removing electroencephalographic artifacts: comparison between ICA and PCA".** In *Neural Networks for Signal Processing VIII. Proceedings of the 1998 IEEE Signal Processing Society Workshop (Cat. No. 98TH8378)* (pp. 63-72). IEEE.

[85] Anderer, P., Roberts, S., Schlögl, A., Gruber, G., Klösch, G., Herrmann, W., ... & Saletu, B. (1999). **"Artifact processing in computerized analysis of sleep EEG–a review".** *Neuropsychobiology*, *40*(3), 150-157.

[86] Chen, X., Xu, X., Liu, A., Lee, S., Chen, X., Zhang, X., ... & Wang, Z. J. (2019). **"Removal of muscle artifacts from the EEG: a review and recommendations".** *IEEE Sensors Journal*, *19*(14), 5353-5368.

[87] Cao, K., Guo, Y., & Su, S. W. (2015, December). **"A review of motion related EEG artifact removal techniques".** In *2015 9th International Conference on Sensing Technology (ICST)* (pp. 600-604). IEEE.

[88] Klekowicz, H., Malinowska, U., Piotrowska, A. J., Wołyńczyk-Gmaj, D., Niemcewicz, S., & Durka, P. J. (2009). **"On the robust parametric detection of EEG artifacts in polysomnographic recordings".** *Neuroinformatics*, *7*(2), 147-160.

[89] Minguillon, J., Lopez-Gordo, M. A., & Pelayo, F. (2017). **"Trends in EEG-BCI for daily-life: Requirements for artifact removal".** *Biomedical Signal Processing and Control*, *31*, 407-418.

[90] Sadiya, S., Alhanai, T., & Ghassemi, M. M. (2021, May**). "Artifact detection and correction in eeg data: A review".** In *2021 10th International IEEE/EMBS Conference on Neural Engineering (NER)* (pp. 495-498). IEEE.

[91] Craik, A., He, Y., & Contreras-Vidal, J. L. (2019**). "Deep learning for electroencephalogram (EEG) classification tasks: a review".** *Journal of neural engineering*, *16*(3), 031001.

[92] Haumann, N. T., Parkkonen, L., Kliuchko, M., Vuust, P., & Brattico, E. (2016). **"Comparing the performance of popular MEG/EEG artifact correction methods in an evoked-response study".** *Computational Intelligence and Neuroscience*, *2016*.

[93] Sazgar, M., & Young, M. G. (2019). **"EEG artifacts".** *Absolute epilepsy and EEG rotation review* (pp. 149-162). Springer, Cham.

[94] Jung, T. P., Makeig, S., Humphries, C., Lee, T. W., Mckeown, M. J., Iragui, V., & Sejnowski, T. J. (2000). **"Removing electroencephalographic artifacts by blind source separation".** *Psychophysiology*, *37*(2), 163-178.

[95] Kaya, I. (2019). **"A brief summary of EEG artifact handling".** *Brain-Computer Interface*.

[96] Taherisadr, M., Dehzangi, O., & Parsaei, H. (2017). **"Single channel EEG artifact identification using two-dimensional multi-resolution analysis"**. *Sensors*, *17*(12), 2895.

[97] Jafarifarmand, A., & Badamchizadeh, M. A. (2019). **"EEG artifacts handling in a real practical brain–computer interface controlled vehicle".** *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *27*(6), 1200-1208.

[98] Gorjan, D., Gramann, K., De Pauw, K., & Marusic, U. (2022). **"Removal of movement-induced EEG artifacts: current state of the art and guidelines"**. *Journal of neural engineering*.

[99] Hartmann, M. M., Schindler, K., Gebbink, T. A., Gritsch, G., & Kluge, T. (2014). **"PureEEG: Automatic EEG artifact removal for epilepsy monitoring"**. *Neurophysiologie Clinique/Clinical Neurophysiology*, *44*(5), 479-490.

[100] Muthukumaraswamy, S. D. (2013). **"High-frequency brain activity and muscle artifacts in MEG/EEG: a review and recommendations".** *Frontiers in human neuroscience*, *7*, 138.

[101] Kang, G., Jin, S. H., Kim, D. K., & Kang, S. W. (2018). T59. **"EEG artifacts removal using machine learning algorithms and independent component analysis".** *Clinical Neurophysiology*, *129*, e24.