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RESEARCH ARTICLE

A STUDY ON EEG ARTIFACT REMOVAL TECHNIQUES

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Abstract

The Electroencephalography (EEG) signals represent the asynchronous electrical activity due to the movement of neurons in the brain. The Electrodes placed upon the scalp are used to measure the small voltage fluctuations that are generated by the ion current flows of active neurons within the brain. EEG has been widely used to analyses brain function. EEG signals are mainly used to treat neurological disorders, in brain Computer Interface (BCI), to detect sleeping disorder, etc., Anyhow the Obtained recorded electrical activity has always been contaminated with different forms of interferences- known as artifacts. They may be both non-physiological and physiological artifacts . In this study, we studied various supervised and unsupervised artifact removal techniques along with their results which were produced by researchers. These techniques were compared based on their performance measures, number of channels and datasets. This paper will present a good resource for various artifact removal techniques.

Index Terms—Artifact removal(AR), Brain computer Interface (BCI), Independent component analysis (ICA), Electroencephalography (EEG).

I. Introduction

The function of the central nervous system (CNS) is to receive inputs from the surrounding of the human bodyand producing outputs that serve the requirements of it. Brain Computer Interface (BCI)is a computerized device, that captures electrical signals of brain and transfigure into various outputs that improve natural CNS output[5]. The main purpose of BCI is to create useful functions for physically challenged people affected by neuromuscular disorders. Human BCI ismainly categorized as Semi-Invasive,Invasive,andNon-Invasive[36][35]. In Invasivetype, microelectrodes are placed directly into the outer cortex of the brain. In semi-Invasive BCI type, the electrodesare partially placedin the brain but rest outside the skull. In Non-Invasive type,the Electrodes are implanted outside the skull.Various Techniques are used in BCIareECoG,MEG, fNIR,MRI,SPECT, fMRI, EEG[6].

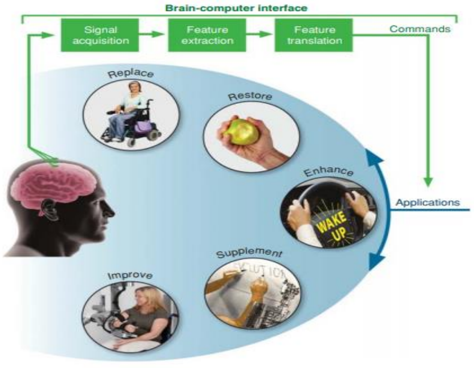

Figure 1. BCI system design and operation.[5]

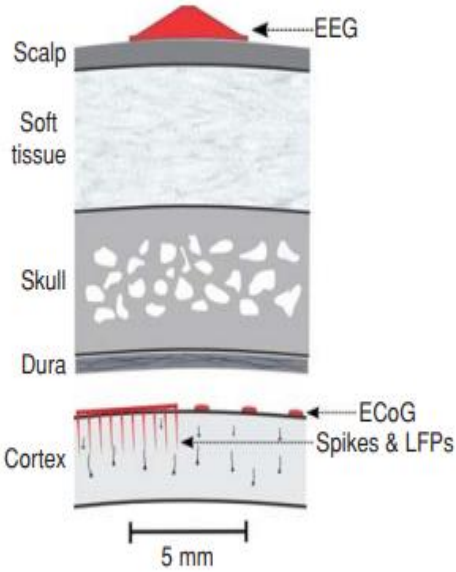

Figure2.EEG Recording sites [8]

Brain activity can be measured by electroencephalograms. EEG is a non-invasive technique, that uses a small flat metal disc called electrodes distributed over the scalp to measure the feeble electrical impulses generated by braincells[9][11].In EEG, various types of electrodes are used such as disposable, reusable, headbands, electrodes caps, saline-based electrodes, needle electrodes.EEG is trustable for real-time applications as it can take very accurate measurements[7].The main problem in EEG is artifacts. The artifacts are unwanted noise recorded in the EEG which has no relation to the interested electrical activity of the brain. Artifacts are mainly two types: physiological and non-physiological artifacts. Physiological artifacts are caused by the human body like eye movements, blinking and other muscular activities and on-physiological artifacts can occurs from outside the body[38].[3] [22][27] [34]

S.No	Artifacts	causes	types	sources
1	Eye blinking	Ocular	physiological	Internal
2	Movement of eyes	Ocular	Physiological	Internal
3	Rapid eye movement in sleep	Ocular	Physiological	Internal
4	Scalp contractions	Muscle	Physiological	Internal
5	Chewing	Muscle	Physiological	Internal
6	Speaking	Muscle	Physiological	Internal
7	EKG	Cardiac	Physiological	Internal
8	Swallowing	Muscle	Physiological	Internal
9	Breathing	Respiratory	Physiological	Internal
10	Skin Response	Skin	Physiological	Internal
11	Sweating	Skin	Physiological	Internal
12	Electrode movements	Instrumental	Non-physiological	External
13	ImpedanceImbalanceofElectrode	Instrumental	Non-physiological	External
14	Movements of Cable	Instrumental	Non-physiological	External

15	Electromagnetic coupling	Electromagnetic	Non-physiological	External
16	Power line	Electrical	Non-physiological	External
17	Head movements	Movement	physiological	External
18	Body movements	Movement	physiological	External
19	Hand	Movement	physiological	External
20	Leg movements	Movement	physiological	External

Table 1 Types of EEG Artifact [10]

To remove OAs, time domain and frequency domain regression techniques are generally used. In these techniques, Electrooculogram (EOG) recording is required and it can also lead to the removal of neural activities [1][2]

PCA, ICA, Kurtosis, and Multiscale sample entropy are effective in OA removal, but these techniques depends on multichannel data. WT is the most promising technique to removeocular artifacts in EEG data from any single channel. DWT is a faster technique requires less computational resources than SWT for realtime analysis[4]

II Methods discussed in this paper

1.**Comparision of various ICA algorithms**[12]

In this paper, various Independent Component Analysis techniques are compared, in terms of performance and computational difficulties.The ICA techniques JADE, CoM2, SOBI, SOB Irob, Info Max, PICA,FastICA, ERICA, SIMBEC, FOBIUMJAD, TFBSS, ICAR3, FOOBI1, and 4-CANDHAPc[12] are thoroughly analyzed.. To measure the performance, all the listed ICA methods are analyzed the simulated EEG signal sand reconstructing the original EEGsignals. CoM2 appears as best of all the ICA methods,CoM2handout better performance and computational abilities, where TFBSS and FOBIUMJAD seem to be a bad choice.

2. **modified Multiscale sample entropy and Kurtosis [13]**

In this paper, the authors proposed a computationally effective stochastic technique to eliminate eye blink-associated independent components. The mMSE and Kurtosis techniques are utilized to distinguish and eliminate the contaminated independent components by using biorthogonal wavelet decomposition. mMSE can effectively find out the ICs with the eye blink features. Kurtosis further improves the achievement by identifying ICs with super Gaussian probability distributions, where the peaked values perfectly resemble the distribution of eye blink. The merit of this method is no manual intervention is needed for execution. The authors show that mMSE and kurtosisis the best stochastic method to remove ocular artifacts.

3.**The event-related feature-based clustering algorithm used to identify artifacts[14]**

The authors proposed a new automated technique to identify physiological and non-physiological artifacts. The identification can be done in two steps. The first step is used to identify physiological artifacts by an event-related feature-based clustering method. In the second step, the electrodes scalp impedance information to identify non-physiological artifacts[14]. This method is highly efficient in improving the quality of ERP and the performance results.This method seems to be superior when compared to other common automatic artifact removal methods. This method is excellently suitable for both physiological and non-physiological artifacts removal. This method feasibly applied in a short time during emergencies.

4.**Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT)[15]**

In this paper, the authors used two unsupervised techniques,DWT and SWT, to remove OA from single-channel EEG data. Apart from the main two techniques, four basic functions of WT are also utilized with the universal threshold (UT) and statistical threshold (ST)[15]. To measure OAs removal efficiency, performance measuring tools like CC, MI, SA ratio, NMSE, and TFwere used.16 combinations were formed between the main two techniques and four basic functions.According to performance measurement, none of the combinations was best in all scenarios. DWT is a faster technique than SWT, which needs low computation time for real-time analysis [4]. If computation time is not restricted, then SWT can be used with the statistical threshold. Identifying and applying the OA removal algorithm only to the blink OA regions, develop a faster OA removal technique, which the authors mentioned previously

5.**Ensemble Empirical Mode Decomposition (EEMD)-Canonical Correlation Analysis(CCA) [16]**

This paper, the authors proposes a non-conventional technique called EEMD-CCA for muscle artifact removal,by merging EEMD and CCA[16]. In this method, two steps are involved. In the first step, the single channel signal is transformed into a multichannel signal[37] X by the EEMD method. In the second step, CCA is applied to the multichannel signal. EEMD collects the IMF from the single-channel data and the CCA analyzes the IMF to find the canonical variables. The EEMD-CCA is always superior to CCA at various SNR values to RRMSE. The results demonstrate the merit of single-channel techniques over multichannel ones, particularly for lower SNR.

6. **Independent Component Analysis and Multivariate Empirical Mode Decomposition[17]**

In this paper, ICA and MEMD were combined used to remove EOAs from multichannel EEG signals. The MEMD technique segregates the EEG signals into various MIMFs. By combining the MIMFs related to EOAs, the components with EOG were collected. Then EOG-related independent components have being found and removed by the analysis of ICA on EOG related components. In the last step, the pure EEG signals were attained by taking inverse transformation of MEMD and ICA .The simulation outcomes showed that this method could effectively remove EOAs from simulated EEG signals along with retain required EEG data with minimal loss. This method attains high SNR and low MSE than the other existing methods.

7.**Singular Spectrum Analysis (SSA) and Adaptive Noise Canceler (ANC)[18]**

The authors present a novel technique merge SSA and ANC to eliminate the EOG artifacts from the impure EEG signal. In this method, SSAis used to collect the reference signal (EOG) for ANC.This method score high performance, since the effectiveness of SSA-ANC, is not dependent upon the structure EOG signal. The simulation results also clearly show that the performance of SSA-ANC is better than DWT-ANC in terms of mean error. The SSA-ANC method is effective for EEG signals from single-channel,so this can be suitable for portable applications.

8.**Penalized semi algebraic unitary deflation (P-SAUD) algorithm[19]**

In this paper, the authors proposed latest ICA technique, called penalized semi algebraic unitary deflation P-SAUD[19] algorithm, that effectively extracts the epileptically components from the contaminated EEG signal. This method minimizes computational difficulties to a great extent with better performance. This can be done by applying the penalized semialgebraic method, which at first allows us to find the source of epileptic activity and avoid the requirements of extracting the epileptic-related components. Even though thistechniquesisrelaed on DelLR'sdeflation scheme, it attains better achievement by incorporating a semialgebraic strategy.

9.**Heuristics Extend Influential Independent Component Analysis [20]**

In this paper, two selfmoving EEG Artifact Removal Techniques are proposed to Detecting Influential Independent Components in multiple artifacts, by using the real and synthetic data set. After analyzing the various artifacts, the spatiotemporal-frequency impact of these EEG artifacts is identified and the proposed two artificial removal techniques clear the corrupted EEG signal. One method is based on the strength of influence of ICA by Pearson correlation and the other is based on Minkowski'ssum.The proposed techniques attain excellent (SNR) in synthetic data and (CSR) scores for all subjects in obtained EEG. The time-frequency analysis of artifact processing and visualization of these methods are also much better than other methods. Based on the results, these methods are capable to rebuild pure EEG signals from the contaminated signals.

10.**Minimum Noise Estimate filter[21]**

The Minimum noise estimate filter, attempt to identify and reduce the noise occurred in the original signal. The minimum noise estimate filter works in twosteps. In the first step, the calculation of noise is found bythe Rayleigh quotient[21]. In the next step, an effective filter is provided to reduce the calculated noise. This filter is potential to analyze the signals without any prerequisites data about signals. MNE filter arranges thesignal sources in a array, which is based on Eigen values.By this arrangement, the source can be easily distinguishableas desirable and undesirable. Hence, no further technique is required to find the sources of artifacts. This method outshines all the other established existing techniques for artifact removal like ICA, CAR, Laplacian,etc.

11.**Surrogate-Based Artifact Removal From Single-Channel EEG[23]**

Surrogate Based Artifact Removal[23] (SUBAR) is a data-driven algorithm for single-channel EEG to muscular artifacts and efficiently eliminate OAs. In this method, EEG embedded with muscular and ocular artifacts can be filtered automatically by means of high frequency methods. Thus, the result is shown in single-channel technique for artifact removal offline sensor. The proposed method is an example for real-time experiment environments, such as emotional states or cognitive mobile monitoring. This method can be well utilized in mobile environment.

12.**Novel Technique for Selecting EMG-Contaminated EEG Channels [24]**

The authors proposed a novel technique for better classes sepeartion and low information loss for selecting EEG Channels Contaminated byartifacts(EEG-CCh). EMG channels and EEG is correlatedwith EMG-CCh.The separate class playsa significant role compared with artifacts (using a Wilcoxon test). The weak EMG removal and reliability test results ensure a promising EEG channel. Thus result shows that EMG-CCh method which is correctly identify channels, but does not affect the class variable results.

13.**MorphologicalComponentAnalysis (MCA) and *K*-means S*ingular Value Decomposition* (*K-SVD)[25]***

The authors introduced new techniques called MCA and k-SVD based on sparsity[25], to eliminate eye blink artifacts from the signals. No need of any additional information about the channels , parameters and equipments in this techniques This method decompose a signal into several parts according to structural features.MCA techniques allow reconstruction separated signal by means of sparse representation.
EEG dataset itself learnsthe K-SVD algorithm and design to simulate EB features. To estimate the sparse Coefficients, the dictionaries are predefined and unaltered in MCA methods. To update a dictionary Matrix , Estimated sparse solution is used in KSVD method. EB artifacts can be estimated by the spare solution and updated dictionary.To get clean EEG data, subtract the EB artifacts from the contaminated EEG signals.

14. Unsupervised artifact detection(AD) and Unsupervised Method for Artefact Removal(UAR)[26]

The authors proposed new unsupervised artifact removal (UAR) Method. It allows automatic individual artifacts using the Fast ICA algorithm and also automatically combine an unsupervised artifact detection (AD).It combines both simulation and real-time data of EEG with artifact (SEEG and AEEG). The signal testing EEG filter with the different types of artifacts in UAR, and can use as an online application filter. The UAR filter is unsupervised, it applies based on the type of artifact filter EEG. To justifying he filtering process a two-sample F-test using the ICs selection.

15.**Multiresolution Total Variation (MTV) and Multiresolution Weighted Total Variation (MWTV) Filtering schemes.**[28]

These methods are based on two filtering schemes.One is MTV and the other is MWTV.To separate EEG signals into various sub-band signals, the multiresolution variation analysis is used.Approximation of the sub-band signal can be done by the TV and weighted TV (WTV). The differed values of the noisy approximation sub-band signals, the yield of the TV and WTV filter are the basis of filtered approximation sub-band signal evaluation. By analyzing all the existing techniques, MTV and MWTV methods posses an excellent denoising performance than others. Calculation difficulties in these methods are lower than the other techniques for motion artifact removal.

16.**VariationalMode Decomposition (VMD) and Turning Point Count[29]**

The authorscame witha new frameworkto indentify and remove OAs.This method is utilizes turning point count and VMD .Non-recursive decomposition technique is recent upcoming technology in VMD.VMD is a pre-defined model with multivariant components. VMD is a limited-edition band called modes ('P') with different densities. In the paper, they proposeda framework effective of VMD in two different stages called stage 1-VMD-1 and stage 2- VMD-11 respectively. EEG signal has four components with two different stages in VMD-1 and VDM-11. EEG signal decomposition various modes using stage 2 to reject the low-frequency components. The mode rejection containing OAs criteria in different turning point counts. The OAs eliminates with minimal loss in the framework, to allow reconstructed EEG signal and method rhythms. This technique perform effective EEG signal analysis in various small application to remove OAs.

17.**Time–frequency (TF) Filtering[30]**

The author proposed a novel TF time-frequency filter, which isolates neural response from artifact due to eye movements in a minimum-density array in temporal and spectral features exploits in the filter. The study presented a novel time-frequency filter technique. It allows to access signals in a minimum-density array to extract the blink oscillation and to remove artifacts comparing only a few electrodes[30].

The channel is applied to every individual data of the time-frequency, which signal relative to ocular in an artifact. This is known as the time-frequency characteristic.EEG signals for the non-stationary allow the analysis of the TFused short-time Fourier transform (STFT). The STFT function separate signal into small segment according to window truncating, which map raw data of STFT domain into a function time and frequency. The results showthis filter is successful in capture and isolatethe blink oscillation by utilizing a four electrode array.

18.**Fourier-Bessel series expansion based empirical wavelet transform (FBSE-EWT)based Rhythms** [31]

The authors discussed , a novel FBSE-EWT technique, which allow separating rhythm-based EEG signal.
The filter is build on the local polynomial approximation based total variation (LPATV) is utilized to improve EEG signal artifact. The artifact compound is obtained used to enhanced LPATV over the Rhythms of the impure signal. The signal obtained from the filter is based on the linear combination between the rhythms. The result shows that performance was measured to evaluate the method in the experimental analysis. We compared with other existing techniques the higher performance over minimum average MAE in PSD value is 0.029.

19.**Recurrent Neural Networks using a Gated-Recurrent Unit (RNN-GRU)**[32]

This study author present a novel a technique, called the filter approach. The recurrent neural network using a gated recurrent unit (RNN-GRU)[32], Which allow to various finite and infinite impulse response (FIR and IIR) filter. For effective machine learning network filtering for EEG signals, the results must be with a loss rate of (MSE)as low as 1.13. In future extracting with a high average accuracy rate using the filter,the approach is combined with ICA and Convolutional Neural Network (CNN) for classification.

20.**Electroencephalography (EEG) and functional magnetic resonance imaging** (fMRI)[33]

The ballistocardiogram (BCG), is developed a novel method to modeling the BCG from ECG by utilizing Recurrent Neural Networks. The large amplitude BCG artifact is resulting from heart related movement contaminates the EEG during the EEG-fMRI recordings. In EEG-fMRI recording, to reduce BCG artificates, the RNN methods used without any extra standard hardware's. We analyze the performance measured over a common optimal basis set (OBS) with different levels of individual function and generalized across a function. Shows this algorithm produce higher average power reduction compared to BCG at critical frequencies**..** At the same timeit boost various task related EEG based classification.

III Comparison Results

Method	Channels	Data Set	Comparison method	Performance measured/indicator	Type of Artifacts	Result
comparative analysis of various ICA methods	Multi channel	Not mentioned	Various IC methods	NMSE	epileptic	CoM2 IS Best
mMSE, Kurtosis, and Wavelet-ICA	Multi channel	4 subjects	Zeroing ICA,wICA	Correlation Coefficient, Mutual Information	eye blinks	Attain 90 % mean sensitivity and 98% mean specificity
Event-related feature-based clustering algorithm	Multi channel	10	k-mean with imilrity, Auto-mutual information,, ADJUST, FASTER	Classification Accuracy	Physiological and Nonbiological artifacts	performance improvements were achieved
Compare Wavelet-Based Techniques	Singe channel	4 subjects	DWT and SWT	correlation coefficients, mutual information, SNR, NMSE, TF analysis.	Ocular Artifact	WT be an excellentmethod to remove OA from single channel EEG recordings
EEMD–CCA	Singlechannel	two real EEG datasets	CCA	RRMSE	for muscle artifact	computationally more efficient and more reliable than EEMD-ICA.
ICA and MEMD	Multichannel	3 Subjects	AWICA, SSA-EMD.	SNR, MSE	EOG Artifacts	Achieved higher SNR

						and lower MSE .
SSA and ANC	Singlechannel		DWT-ANC	RRMSE and MAE.	EOG Artifacts	Capable to analyze single channel EEG signals.
P-SAUD	Multi channel	3 Subject	CCA, SOBI, Fast ICA, CoM2 ,DelLR.	Not mentioned	epileptic sources	Reduced computational cost
heuristics extend influential ICA		6 subjects	MARA,, ADJUST, FASTER, wICA	SNR, clutter-to-signal ratio (CSR)	Artifactslikeeye Blinking, Horizontal Eye movements, Swallowing,head shaking,	achieved a betterSNR and CSR score
MNE filter	Multi channel	2 pre-recording datasets	CAR, Laplacian, ICA and wavelet denoising.	correlation coefficients	Chewing artifacts	Economical online application compare to other denoising technique
Surrogate-Based Artifact Removal From Single-Channel EEG	Single-Channel	3 Subjects	wavelet thresholding, CCA combined with the EMD.	(RRMSE) RRMSE for different SNR	Ocular artifacts, Muscular artifacts,	Better for removingphysiologicalfrom single EEG signals.
EMG-CCh	Multi channel	5 subjects	BSS-CCA, ICA and PCA	Davies-Bouldin Index (DBI)	EMG artifact	correctly identifying channels that could affect class dependent results.
MCA and *K-SVD*	Multi channel	7 subject	(FORCe)	average RMSE, CC, SAR, and MI	Eye Blink Artifacts	Do not need any channel data or additional equipment
AD_UAR	Multi channel	Not mentioned	MARA, SASICA, and wICA.	AEEG and SEEG. Filtering.	Jaw Clench, and Movement, Eye Blinks, and Movements	Capable to filter any artifact
MTVand (MWTV) filtering schemes	Single channel	public database physionet	DWT and thresholding, EMD and IMF selection, EEMD and	SNR, correlation coefficients (η)	motion artifact	Calculating difficulty in these approaches is lower than the existing

			IMF selection, EMD-ICA, EMD-CCA, EEMD-ICA ,EEMD-CCA, SSA			techniques
VMD and turning point count	Single Channel	3 Databases namely,Mendeley, Polysomnographic, EEGMAT	DWT-UT, DWT-ST, SavitzkyGolay(SG) filter	NCC,SNR, MAE,MAX, NMAX,NRD, PRD,RMSE	Ocular Artifact	Perform accurate EEG analysis in different portable systems
TF filtering	Multi Channel	31 SUBJECTS	Morphological comparison	INTRACLASS CORRELATIONS	ocular artifacts by eye movements	low-density electrode array is used for first time to capture and isolation of ocularresponse
FBSE-EWT	Single Channel	27 subjects	Wvelet sym3, DWT-ANC, EEMD-PCA, EEMD-KPCA, SSA-ANC, DWT-ICA	ER values, MAE on PSD values	Ocular Artifacts	Excellent result with less average MAE.
RNN-GRU	Multi channel	10 subjects.	Butterworth-4, Belwafi's, Adaptive filtering, COWA	Sensitivity, specifity, accuracy	epilepsy	combining ICA and CNN attained High average accuracy rate
RNNs	Multi chnnel	25 subjects	Optimal Basis Set (OBS) method		BCG artifact	To suppress the artifacts, deep learning approach can be used with no additional hardware.

Table-2 Comparison of Artifact removal techniques and their results

IV Conclusion

Even though so many numbers of artifact removal methods and techniques are available, the artifact elimination problem is still difficult for many applications. For some simple applications, we can easily tackle them by taking measures such as artifact avoidance and artifact rejection. But in many cases, we need complicated methods and techniques to deal with artifacts to minimize their effects on EEG signals. A single unique solution for all types of artifacts removal problems is not found yet. we must select a suitable method to remove artifacts by considering so many factors like artifact type, channel type, underlying sources, the contamination level of the signal, muscle activities, condition of equipment, etc. In future, we must focus our attention to develop specific application oriented techniques with excellent efficiency, by combining modern ideas like machine learning with existing traditional approaches for automatic artifact removal . In this paper we studied various supervised and unsupervised artifact removal techniques along with parameters like performance measures , number of channels, datasets and their results.

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