iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 5 **Issue:** X **Month of publication:** October 2017

DOI: http://doi.org/10.22214/ijraset.2017.10149

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue X, October 2017- Available at www.ijraset.com

Study of Various Automatic EEG Artifact Removal Techniques

Anshul Khatter[1], Dipali Bansal[2], Rashima Mahajan[3]
[1]*PhD Scholar, ECE Department, Manav Rachna International University, Faridabad*
[2]*HOD & Professor, ECE Department, Manav Rachna International University, Faridabad*
[3]*Associate Professor, ECE Department, Manav Rachna International University, Faridabad*

Abstract*: In recent researches, Electroencephalography (EEG) gains a widespread popularity. There is maximum probability of artifact with EEG signal because of physical and experimental problems therefore artifact elimination is a central issue during encephalogram recordings. Although many researchers have doing research in this area and developed their own method for artifact elimination like independent component analysis (ICA), average artifact subtraction (AAS), real time independent component analysis (ICA), Recursive Least Squares (RLS) adaptive filter, Spatially Constrained Independent Component Analysis(SCICA), Blind Source Separation and Wavelet Denoising, still visual examination by experts is needed. Finding the artifacts and eliminating them from real EEG signal by the use of competent algorithm assists researchers and doctors. This paper discusses the various methods along with limitations of automatic EEG artifact removal techniques.
***Keywords*: Electroencephalography, Adaptive Filter, Artifact, Independent Component Analysis, Artifact Removal Techniques**

I. INTRODUCTION

The electroencephalogram (EEG) imitates states of brain allied to the person's mental condition. Due to the temporal resolution of EEG, it is considered to be an outstanding and extensively used for exploring functioning of human brain. A main difficult in this is the various artifacts occurred in EEG signal like movements of eye, blinks, activity of muscle, heartbeat, line noise, high electrode impedance and meddling from electric devices. [T.Raduntz, 2015]. The elimination of artifact in EEG is essential and becomes problematic if very few eras are there. Artifacts are divided in two categories: Physiological and Non-Physiological. Main causes of occurrence of Physiological artifacts are patient moving the head, Eye blinks, sweating, Eyeball rotation, heart beat and Muscle contraction and the main causes of occurrence of Non-Physiological artifacts are external faults example electrode failure, ventilation and power supply. As Ocular artifacts have same frequency as of EEG signals therefore problematic to identify therefore competent algorithms are required to eliminate the artifacts. [P Bhuvaneswari et al.,2012]. These methods are discussed in Section2

II. RELATED WORK

Many methods are used by researchers for eliminating artifacts like independent component analysis (ICA), average artifact subtraction (AAS), real time independent component analysis (ICA), Recursive Least Squares (RLS) adaptive filter, Spatially Constrained Independent Component Analysis (SCICA), Blind Source Separation and Wavelet Denoising.

Sim Kuan Goh, 2017, uses EEG data to project indicators which will act as substitutions for sensing individual's cerebral activities. These electrical signals contain artifacts which significantly obscure the useful information in the signal. An operative artifact removal technique (ART) which eliminates or reduce the influence of the artifacts. A variety of eight dissimilar and distinctive artifacts which occur practically is examined using this technique. The spatiotemporal-frequency characterizes effects artifacts and offers two solutions. The offered solution prolonged significant independent component analysis to eliminate the artifacts from EEG signal and then by the use of real and synthesized EEG data, these proposed solutions are compared with four EEG ARTs. The result shows that in automatic artifact removal both solutions proposed better spatiotemporal-frequency performance. Two offered ARTs attained a better signal-to-noise ratio in synthesized data and superior clutter-to-signal ratio score for acquired EEG .The result also shows improved artifact processing in time and frequency exploration and idea for other 8 categories of artifacts. This study eases consistent experimental EEG investigation and robust Brain Computer Interface system.

A. Comparison to other studies this study achieves following advantages:

The spatiotemporal-frequency effect of EEG artifacts which are collected from 8 designed experimental setups are described
Current automated artifact elimination methods in the setup of multiple artifacts by both acquired and synthesized EEG are assessed

Proposed new artifact elimination techniques, for numerous types of artifacts in the multiple artifacts scenarios, which have less restrictive previous supposition on artifact features.

The limitations in their study are:

Effect of the artifact elimination techniques which combine Blind Source Separation and wavelet/ empirical mode decomposition, are not reported.

Alaa Eldeen M. Helal et al., 2017, proposed extensive method grounded on Template Matching approach with multiple signal-processing tools. The technique was assessed and authenticated on real EEG records and results show this technique has improved competences in routine EEG studies and analysis. The spectral, temporal and frequency features of the extracted segments were evaluated and develop specific, distinct artifact samples for every type. By comparing the dissimilar features to that of the verified EEG windows automatically and eliminate the analogous ones, residual were simply the pure signals. Combining the consequences of all artifact types, altogether performance was 88.09% specificity and 89.438% sensitivity.

1) The limitations in their study are

a) The performance of algorithm was assessed on inadequate data sets.

b) The parameters were evolved as per visual analysis by EEG specialists, using the True Scan EEG system in which human inaccuracy for the period of this manual examination cannot be overlooked.Malik M. Naeem Mannan et al.,2016, proposed a hybrid framework which mixes independent component analysis (ICA), regression and high-order data for identification & removal of artifacts from EEG data. To assess and then to analyze the usefulness of this proposed technique, along with simulated EEG signal, experimental and standard EEG signals are also used . The results are compared with four other existing methods: ICA, wavelet-ICA(wICA),regression analysis and regression ICA (REGICA) .The analysis demonstrates that the proposed technique can efficiently eliminate ocular artifacts and it preserves the activity of neuronal linked with EEG signals.T.Raduntz et al. in 2015 proposed an innovative methodology grounded on machine classification of Independent components (ICs) as artifact or EEG signal by features grown through image processing algorithms. To analyze this method, visually assessment of 2D scalp map projections of the ICs, named topoplots, is done. As real-life EEG data includes an assortment of artifacts with unidentified properties that's why an automated method is developed which is accomplished of differentiate among the pure EEG signal and all kinds of artifacts. A classification valuation using the mixing matrix columns is done and result shows 87.7% of recognition rates which validates the concepts of using the interpolated images, which intrinsically use the mixing matrix columns for classifier training. This approach does not dependent on quantity of EEG channels used; it also carries out for every EEG channel locations, and no need to be retrained. An automatic artifact removal by linear discriminant analysis (LDA) aimed for classification of feature vectors take out from independent component analysis (ICA) components was achieved. Nearly the similar recognition performance was achieved for both the features: geometric and local binary pattern. As compared to any surviving automated solutions this technique has advantages

It was independent from direct recording of artifact signals

It was not restricted to quantity of EEG channels used or kind of artifact. Flexibility to number of EEG channel used makes this method as universal and not limited to type of artifacts, makes it capable to apply online on diverse experiments and subjects. The manual classification done by experts may marginally vary among each other (Winkler et al., 2011) therefore there might be differences in SNRs among expert and machine de-noising.

2) The limitations in their study are:

a) More precise classification results were succeeded if, for successful system training, an average rating of more than two experts would be considered.

b) With the same classification rate, the computational exertion can be decreased by down sampling.

c) By merging the image features with frequency information and by applying non-linear classifiers like support vector machine, the results can be improved.

ZhenYu Wang et al., 2014, state ocular artifact can totally distort EEG data so it's essential to efficiently eliminate the ocular artifact without any loss of valuable EEG information. They proposed a new method of merging ICA and Auto-Regressive eXogenous (ICA-ARX) to eliminate ocular artifact. ICA persuades a negative effect which is decreased by the use of ARX. ARX construct the multi-models grounded on the corrected signals of ICA and the selected reference EEG before polluted time for every channel, after that the ideal model would be carefully chosen for additional artifact elimination. The algorithm was applied to the simulated as well as the actual EEG recordings and the result shows this method is useful for ocular artifact elimination.

3) The limitations in their study are: ; Only ARX alteration for fastICA are considered, without examine their performances when various ICA variants are collective with ARX for EOG artifact alteration.

Carlos Guerrero-Mosquera et al., 2009, proposed a technique to eradicate eye movement artifacts (EOG) which is grounded on Independent Component Analysis (ICA) and Recursive Least Squares (RLS). In this algorithm, effective ICA capability of sorting out artifacts from brain waves and the online interference cancellation succeeded by adaptive filtering is combined. The distinct electrodes situated near the eyes are used to record vertical and horizontal movements of eyes, so as to excerpt a reference signal. Every reference input is predicted into ICA field, after that the interference is assessed by the use of RLS algorithm and then in the ICA domain, the assessed interference is deducted from the EEG components. The results obtained from experimental data validates that this methodology is appropriate for eradicating eye movements artifacts. The ideology of given method can be prolonged to various other sources of artifacts as well.

4) *The limitations in their study are:*

a) More analysis is required to analyze distortion or association among corrected EEG and original EEG.

b) Extension of the technique is required to pure on-line scenarios.

P Bhuvaneswari et al. in 2012 said that manual artifact identification takes more time while automatic identification and elimination technique will be fast but there is a risk of data loss. So, a competent algorithm is necessary for detection of artifact. The various methods are analyzed for elimination of artifacts from EEG signals. Result shows that out of analyzed various techniques; Independent Component Analysis is one of the commonly used techniques with high accuracy for detection and elimination of artifact.

Samaneh Valipour et al., 2015, discuss the several existing authenticated presented criteria for considering the competence of the Ocular Artifacts (OA) elimination algorithms. All metrics are measured in the MATLAB. Analysis shows some of these criteria are usually used for both real and simulated signals. The analysis shows that assessment of a simulated signal is easier than a real signal. The result also shows that as real EEG signals are nonstationary in nature, by applying the algorithm on same EEG data, the comparison of one algorithm with another algorithm will be significant.

Ahmed Kareem Abdullah et al., 2014, proposed an automatic artifact removal system which is grounded on a mixing of Stone's Blind Source Separation (BSS) and inherited algorithm. The proposed hybridization is named as evolutionary Stone's BSS algorithm (ESBSS). Initially in Stone's BSS short term half-life and long term half-life parameters are used as constant values, and the variations in these parameters will be disturbing straightly the separated signals. The genetic algorithms are an appropriate method to overwhelm the existing problem by concluding arbitrarily the best half-life parameters in Stone's BSS. This system automatically extracts the common artifacts for example heart beat and ocular artifacts. No notch filter is used in this system therefore useful information is not loss. The proposed automatic artifact removal system is verified best for sub-Gaussian signal and super-Gaussian signal from brain EEG blended automatically and simultaneously. ESBSS was exposed to accomplish superior than various kinds of blind source separation algorithms as verified in simulated and experimental results. The obtained results of ESBSS algorithm are inspiring and are used to remove other kinds of artifacts.

Vipul D.Sanjana et al., 2015, offered a technique, to identify Ocular Artifact zone and construct reference signal, in which Discrete Wavelet Transform (DWT) is used with Adaptive method. Adaptive Noise canceller is vigorously cancelling Ocular Artifact (OA) from EEG signal by the use of reference and primary channel. DWT is used as filter bank which identifies low frequency zone in which Ocular Artifact is greatly affected. Thresholding procedure is used to eliminate noise in primary way but indecorous selection of threshold value might be responsible for removing true EEG signal. This proposed technique is mixing of two techniques in which appropriate choice of forgetting factor offers outstanding result for OA removal and getting true EEG. The analysis shows that forgetting factor which is near to unity offer good performance to eliminate OA as comparison to Least Mean Square algorithm.

G.Geetha et al., 2012, offers an innovative method for eliminating the artifacts from the EEG signals. Artifacts in EEG are of many types for example line interference, electrooculogram (EOG) and electrocardiogram (ECG). The removal of artifact from EEGs is of significant for each the automatic and visual study of EEG signals. The spatially-Constrained Independent Component Analysis (SCICA) is used to detach the Independent Components from the preliminary EEG signal then Wavelet Denoising technique is used to excerpt the brain activity from eliminated artifacts and lastly the artifacts are anticipated back and deducted from EEG signals so as to obtain clean EEG data. For this otsu thresholding technique is used to defining the artifacts. The experimental results illustrates that this method is better for elimination of artifacts than other existing methods.

M. Chavez et al., 2017, recommended an innovative data-driven algorithm surrogate based artifact removal (SuBAR) to efficiently eradicate, to categorize and filter automatically ocular artifacts and muscular artifacts from single-channel electroencephalography. The results of relative study with the use of artificially EEG signals with artifact shows that in context of noise elimination and signal distortion the efficiency of this process was much better than any other traditional single-channel EEG denoising methods. This method is also efficient in the existence of slight and severe artifacts. The analysis shows that SuBAR is an auspicious

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue X, October 2017- Available at www.ijraset.com

technique for portable environments, where insufficient EEG channels are available. The efficiency of the process was compared with the use of artificial EEG artifacts to wavelet thresholding and the Canonical correlation analysis joint with empirical mode decomposition. When this technique is applied to artifact-free EEG sections it provides minimum distortion of the signals. The obtained result recommends that this single channel method is a decent filter for artifact elimination in off-line situations with fewer sensors.

5) The limitations in their study are:

a) As spectrum of impure EEG is same as of a stationary process, this method could not detect the long and tenacious muscular artifacts.

b) In the area of wavelet, decomposition of impure signals could not be distinguished from EEG surrogates with large ocular artifacts.

Chi Zhang et al., 2015, proposed an instinctive online artifact elimination technique grounded on a priori information of artifact. The blending of independent component analysis (ICA), discrete wavelet transform and wavelet-ICA, was used to detached components of artifact. The key idea of this technique was to obtain the online a priori information of artifact and situate them in Wavelet independent component analysis (WICA) with the data which includes artifact. The components of artifact were acknowledged and detached by sorting the association of the noticeable a priori information of artifact and WICs. Here, eye rolling, eye blinking and teeth gritting was used to produce a priori electrooculography and electromyography artifact information. The results exhibited that by the use of this technique classification accuracies improved in both experiments: emotion recognition and motor imagery. Comparison of WICA with other ICA technique shows WICA enhances the performance of ICA, as WICA moves data into some new space where there is more redundancy and the artifacts features are fully used. .

The limitations in their study are:

c) As there is limited number of WICs, too many components of artifact removal lead to the extra removal of artifact.

d) Only works on WICA, so it cannot be determined that whether other methods of ICA works in different situations or not.

e) Focused was only on automatic online removal methods of artifact so less has been achieved in classification and feature extraction techniques, which can disturb the classification accuracies.

Table 1: Literature survey on various techniques of EEG artifact elimination

f)

Title of Paper/Year	Author	Technique	Application	Useful Features of Technologies	Limitations
Automatic EEG Artifact Removal Techniques by Detecting Influential Independent Components (2017)	Sim Kuan Goh, Hussein A. Abbass, Kay Chen Tan, Abdullah Al-Mamun, Chuanchu Wang and Cuntai Guan	An operative artifact removal technique (ART) which eliminates or reduce the influence of the artifacts. A variety of eight dissimilar and distinctive artifacts which occur practically is examined using this technique. The spatiotemporal-frequency characterizes effects artifacts and offers two solutions. The offered solution	Two offered ARTs attained a better signal-to-noise ratio in synthesized data and superior clutter-to-signal ratio score for acquired EEG .The result also shows improved artifact processing in time and frequency exploration and idea for other 8 categories of artifacts. This study eases consistent experimental EEG investigation and robust Brain Computer	The spatiotemporal-frequency effect of EEG artifacts which are collected from 8 designed experimental setups are described Current automated artifact elimination methods in the setup of multiple artifacts by both acquired and synthesized EEG are assessed Proposed new artifact elimination techniques, for numerous types of artifacts in the multiple artifacts scenarios, which have less restrictive previous supposition on artifact features.	Effect of the artifact elimination techniques which combine Blind Source Separation and wavelet/ empirical mode decomposition, are not reported.

		prolonged significant independent component analysis to eliminate the artifacts from EEG signal and then by the use of real and synthesized EEG data, these proposed solutions are compared with four EEG ARTs.	Interface system.		
A Hybrid Approach for Artifacts Removal from EEG Recordings(2017)	Alaa Eldeen M. Helal, Ahmed Farag Seddik, Ayat Allah F. Hussein	Widespread method grounded on Template Matching approach with multiple signal-processing tools. The technique was assessed and authenticated on real EEG records and results show this technique has improved competences in routine EEG studies and analysis. The temporal, spectral and frequency characteristics of the extracted segments were analyzed to get precise, discrete artifact samples for each type.	Cosine Similarity, Wavelet Transform (sym 8) and Independent Component Analysis (FASTICA) are amalgamated to identify dissimilar 15 types of artifact. A latest application of Cosine Similarity in the arena of EEG processing was used to detect any same type of samples to templates of artifact.	Combining the consequences of all artifact types, altogether performance was 88.09% specificity and 89.438% sensitivity Investigating EEG signal in an extensive agenda together with frequency, temporal and spatial fields gives a noble way to capture various EEG artifacts by overwhelming its chaotic and nonlinearity natural surroundings, fast convergence rate	The performance of algorithm was assessed on inadequate data sets. The parameters were evolved as per visual analysis by EEG specialists, using the True Scan EEG system in which human inaccuracy for the period of this manual examination cannot be overlooked.
Surrogate-based artifact removal from single-channel EEG(2017)	M. Chavez, F. Grosselin, A. Bussalb, F. De Vico Fallani,X. Navarro-Sune	An innovative method surrogate based artifact removal (SuBAR) for automatic elimination of	Proposed technique is useful for portable environments, like sleep stage scoring ,	In the occurrence of mild and severe artifacts also, this artifact elimination method gives a relative error nearly 4-5 times less than any other traditional methods.	As spectrum of impure EEG is same as of a stationary process, this method could not detect the long and tenacious muscular artifacts.

		artifact in single-channel EEG was offered. This technique was compared with wavelet thresholding and the canonical correlation analysis combined with an advanced version of the empirical mode decomposition	ambulatory healthcare systems or anesthesia monitoring		In the area of wavelet, decomposition of impure signals could not be distinguished from EEG surrogates with large ocular artifacts.
EEG artifact elimination by extraction of ICA-component features using image processing algorithms(2015)	T. Radüntz, J. Scouten, O. Hochmuth, B. Meffert	To detached data in linearly independent components (IC) ,Independent component analysis was used and automated artifact elimination using linear discriminant analysis (LDA) was done for classification of feature vectors extracted from ICA components by image processing algorithms.	Proposed EEG artifact removal method is universal as it does not depend on quantity of EEG channels used and it achieves for any positions of EEG channel.	The method decreases the time required for manual selection of ICs for artifact removal. The approach was vigorous and automated Which was independent of direct recording of artifact signals and this method is not restricted to a number or type of artifact.	More precise classification results were succeeded if, for successful system training, an average rating of more than two experts would be considered. With the same classification rate, the computational exertion can be decreased by down sampling. By merging the image features with frequency information and by applying non-linear classifiers like support vector machine, the results can be improved.
Automatic Removal Of Ocular Artifacts From EEG Data Using Adaptive Filtering And Independent Component Analysis(2009)	Carlos Guerrero-Mosquera, Angel Navia Vazquez	An adaptive filtering is applied to EEG data components which are obtained by ICA for eradicating EOG contamination. Scalp topographic	Adaptive filtering grounded on ICA is helpful in long recordings and on-line examination and to the eradication of EOG signals, Proposed technique can be applied in artifacts which are	Proposed technique is easy to implement, stable with a low computational cost. This method uses ICA components as reference inputs instead of noise which we need to eliminate.	More analysis is required to analyze distortion or association among corrected EEG and original EEG. Extension of the technique is required to pure on-line scenarios.

		map is used to examine the correspondence of the reference electrodes with EOG artifacts	more difficult to overpower like muscle or electrodes artifacts.		
Automatic Artifact Removal from Electroencephalogram Data Based on A Priori Artifact Information(2015)	Chi Zhang, Li Tong, Ying Zeng, Jingfang Jiang, Haibing Bu, Bin Yan, and Jianxin Li	The online artifact elimination technique grounded on a priori information of artifact was proposed. The blending of independent component analysis (ICA), discrete wavelet transform and wavelet-ICA, was used to detached components of artifact	Situations where a priori information of artifact is acquired grounded on the quantity of channels, the impact of the artifact in the experimentation	No reference channels, visual Inspections massive training samples was required means this method is totally automatic.	As there is limited number of WICs, too many components of artifact removal lead to the extra removal of artifact. Only works on WICA, so it cannot be determined that whether other methods of ICA works in different situations or not. Focused was only on automatic online removal methods of artifact so less has been achieved in classification and feature extraction techniques, which can disturb the classification accuracies.
Robust removal of ocular artifacts by combining Independent Component Analysis and system identification(2014)	ZhenYu Wang, Peng Xu, TieJun Liua, Yin Tian, Xu Lei, DeZhong Yao	They proposed a new method of merging ICA and Auto-Regressive eXogenous (ICA-ARX) to eliminate ocular artifact.	ICA persuades a negative effect which is decreased by the use of ARX. ARX construct the multi-models grounded on the corrected signals of ICA and the selected reference EEG before polluted time for every channel, after that the ideal model would be carefully chosen for additional artifact elimination	The algorithm was applied to the simulated as well as the actual EEG recordings and the result shows this method is useful for ocular artifact elimination.	Only ARX alteration for fastICA are considered, without examine their performances when various ICA variants are collective with ARX for EOG artifact alteration.

III.CONCLUSIONS

In this paper broad literature has been reviewed to sightsee various methods of EEG artifact removal. Artifact removal is a stimulating field in real world environment. Various methods are independent component analysis (ICA), average artifact subtraction (AAS), real time independent component analysis (ICA), Recursive Least Squares (RLS) adaptive filter, Spatially Constrained Independent Component Analysis (SCICA) and Wavelet Denoising, Blind Source Separation. Limitations of already existing work in this field has been tinted which shall act as a ground for further research. The existing algorithms can be efficiently executed for several applications that involve a real-time EEG signal with artifacts suppressed.

REFERENCES

[1] Ahmed Kareem Abdullah, Chao Zhu Zhang, Ali Abdul Abbas Abdullah, Siyao Lian, "Automatic Extraction System for Common Artifacts in EEG Signals Based on Evolutionary Stone's BSS Algorithm" , Hindawi Publishing Corporation Mathematical Problems in Engineering, 2014, Article ID 324750, pp. 1-25.

[2] A. K. Abdullah and Z. C. Zhu, "Blind source separation techniques based of brain computer interface system: a review," Research Journal of Applied Sciences, Engineering and Technology, 2014, vol. 7, pp. 484–494.

[3] A. K. Abdullah, Z. C. Zhu, L. Siyao, and S.M. Hussein, "Blind source separation techniques based eye blinks rejection in EEG signals," Information Technology Journal,2014, vol. 13, pp. 401–413Alaa Eldeen M. Helal, Ahmed Farag Seddik, Ayat Allah F. Hussein, "A Hybrid Approach for Artifacts Removal from EEG Recordings",2017, International Journal of Computer Applications,Volume 168 ,No.4, pp.10-19

[4] Akhtar, Muhammad Tahir, Mitsuhashi, Wataru, & James, Christopher J., "Employing spatially constrained ICA and wavelet denoising, for automatic removal of artifacts from multichannel EEG data", Signal Processing,2012,vol. 92, no.2, pp.401-416.

[5] Alexander J. Casson, David C. Yates, Shelagh J.M. Smith, John S. Duncan, Esther Rodriguez-Villegas, " Wearable electroencephalography",IEEE Engineering in Medicine and Biology Magazine,2010, vol. 29,no. 3, pp. 44-56.

[6] Ameera X.Patel, PrantikKundu,Mikail Rubinov, P. Simon Jones, Petra E.Vértes, Karen D.Ersche, JohnSuckling,Edward T.Bullmore, "A wavelet method for modeling and despiking motion artifacts from 12 resting-state fMRI time series",2014,Neuroimage,vol. 95, pp. 287-304.

[7] Andrea Mognon , Jorge Jovicich, Lorenzo Bruzzone, Marco Buiatti, " ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features", Psychophysiology, 2011,vol. 48, no. 2, pp: 229-240.

[8] Arun KumarAniyan, Ninan SajeethPhilip, Vincent J.Samar, James A.Desjardins, Sidney J.Segalowitz., "A wavelet based algorithm for the identification of oscillatory event-related potential components", Journal of Neuroscience Methods, 2014,vol. 233, pp. 63-72.

[9] B. S. Raghavendra and D. N. Dutt, "Wavelet enhanced CCA for minimization of ocular and muscle artifacts in EEG," World Academy Science Engineering Technology, 2011,vol. 57, pp. 1027–1032.

[10] T. Raduntz, J. Scouten, O. Hochmuth, B. Meffert, "EEG artifact elimination by extraction of ICA-component features using image processing algorithms" Journal of Neuroscience Methods(Elsevier) Vol. 243 (2015),pp. 84–93, http://dx.doi.org/10.1016/j.jneumeth.2015.01.030

[11] Carlos Guerrero-Mosquera, Angel Navia Vazquez, "Automatic removal of ocular artifacts from EEG data using adaptive filtering and Independent Component Analysis," 2009 17th European Signal Processing Conference, Glasgow, 2009, pp. 2317-2321.

[12] Til Ole Bergmann , Anke Karabanov, Gesa Hartwigsen, Axel Thielscher, Hartwig Roman Siebner, "Combining non-invasive transcranial brain stimulation with neuroimaging and electrophysiology: Current approaches and future perspectives" 2016, NeuroImage (Elsevier)Volume140, pp. 4–19 http://dx.doi.org/10.1016/j.neuroimage.2016.02.012

[13] Winkler I, Haufe S, Tangermann M. , "Automatic classification of artifactual ICAcomponents for artifact removal in EEG signals. "Behav Brain Funct 2011,http://dx.doi.org/10.1186/1744-9081-7-30.

[14] Nigel C. Rogascha, Caley Sullivanb, Richard H. Thomsonb, Nathan S. Rosec, Neil W. Baileyb,Paul B. Fitzgeraldb, Faranak Farzand, Julio C. Hernandez-Pavone, "Analysing concurrent transcranial magnetic stimulation and electroencephalographic data: A review and introduction to the open-source TESA software" ,2017, NeuroImage, Volume 147 ,pp. 934–951.

[15] Satheesh Kumar, J., and Bhuvaneswari, P., Analysis of Electroencephalography(EEG) Signal and its categorization –A Study,2012, Elseveir Engineering Procedia.

[16] Eleni Kroupi, Ashkan Yazdani, Jean-Marc Vesin, Touradj Ebrahimi.: Ocular Artifact Removal from EEG: A comparison of subspace projection and adaptive projection methods, Proceedings of 19 European Signal Processing Conference,(2011)

[17] P Bhuvaneswari, J. Satheesh Kumar , "Methods used for Identifying EEG Signal Artifacts", 2012 ,Elsevier.

[18] Samaneh Valipour, G. R. Kulkarni and A. D. Shaligram, "Study on Performance Metrics for Consideration of Efficiency of the Ocular Artifact Removal Algorithms for EEG Signals" ,2015, Indian Journal of Science and Technology, Vol. 8(30).

[19] Vipul D. Sanaja, Vinod Kumar P. Patel, " A combination of RLS algorithm with Wavelet transform for Detection and Removal of OA from EEG signal" , 2015,American International Journal of Research in Science, Technology, Engineering & Mathematics, Vol. 10(2), pp. 161-165

[20] G.Geetha, S.N.Geethalakshmi, "Artifact Removal from EEG using Spatially Constrained Independent Component Analysis and Wavelet Denoising with Otsu's Thresholding Technique", 2012,Procedia Engineering 30,(Elsevier) ,pp 1064-1071

[21] Sim Kuan Goh, Hussein A. Abbass, Kay Chen Tan, Abdullah Al-Mamun, Chuanchu Wang and Cuntai Guan, "Automatic EEG Artifact Removal Techniques by Detecting Influential Independent Components"2017, IEEE Transactions on Emerging Topics in Computational Intelligence, Vol. 1, No. 4, pp.270-279

[22] M. Chavez,F. Grosselin, A. Bussalb, F. De Vico Fallani, X. Navarro-Sune, "Surrogate-based artifact removal from single-channel EEG" ,2017,Physics DataAnalysis.
arXiv:1704.07603

[23] J. A. Uriguen and B. Garcia-Zapirain, "EEG artifact removal -State-of-the-art and guidelines", 2015,Journal of Neural Engineering, vol. 12, no. 3.

[24] K. T. Sweeney, T. E. Ward and S. F. McLoone, "Artifact removal in physiological signals{practices and possibilities", , 2012,IEEE Transactions on Information Technology in Biomedicine, vol. 16, no. (3), pp. 488-500.

[25] K. T. Sweeney, et al. , "A methodology for validating artifact removal techniques for physiological signals",2012, IEEE Transactions on Information Technology in Biomedicine, vol. 16, no. 5, pp. 918-926.

[26] X. Chen, et al. (2016). "Removing Muscle Artifacts From EEG Data: Multichannel or Single-Channel Techniques?", 2016,IEEE Sensors Journal, vol. 16, no. 7, pp. 1986-1997.

[27] J. Gao, C. Zheng, and P. Wang, "Online removal of muscle artifact from electroencephalogram signals based on canonical correlation analysis", 2010, Clinical EEG and Neuroscience, vol. 41, no. 1, pp. 53-59.
[28] K. T. Sweeney, S. F. McLoone and T. E.Ward, "The use of ensemble empirical mode decomposition with canonical correlation analysis as a novel artifact removal technique",2013,IEEE Transactions on Biomedical Engineering, vol. 60, no. 1, pp. 97-105, 2013.
[29] S. Khatun, R. Mahajan and B. I. Morshed, "Comparative Study of Wavelet-Based Unsupervised Ocular Artifact Removal Techniques for Single-Channel EEG Data", 2016, IEEE Journal of Translational Engineering in Health and Medicine, vol. 4, pp. 1- 8.
[30] X. Chen, et al., A preliminary study of muscular artifact cancellation in single-channel EEG", Sensors, vol. 14, no. 10, pp. 18370-18389, 2014
[31] V. Mihajlovi_c, et al., "Wearable, wireless EEG solutions in daily life applications: what are we missing?", IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 1, pp. 6-21,2015.
[32] M. I. Al-Kadi, et al., "Compatibility of mother wavelet functions with the electroencephalographic signal," in 2012 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES), pp. 113-117, 2012
[33] D. Sa_eddine, et al., "Removal of muscle artifact from EEG data: comparison between stochastic (ICA and CCA) and deterministic (EMD and wavelet-based) approaches",EURASIP Journal on Advances in Signal Processing, vol. 1, pp. 1-15, 2012.
[34] Y. Chen, et al., "The removal of EMG in EEGby neural networks", Physiological Measurement, vol. 31, no. 12, 2010.
[35] P. Borgnat, et al., "Testing stationarity with surrogates: A time-frequency approach", IEEE Transactions on Signal Processing,vol. 58, no. 7, pp. 3459-3470, 2010
[36] M. K. Islam, A. Rastegarnia, and Z. Yang, "A Wavelet-Based Artifact Reduction from Scalp EEG for Epileptic Seizure Detection", IEEE Journal of Biomedical and Health Informatics, vol. 20, no. 5, pp. 1321-1332, 2016
[37] M. E. Torres et al., "\A Complete Ensemble Empirical Mode Decomposition with adaptive noise," in 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 4144-4147, 2011
[38] M. A. Colominas, G. Schlotthauer and M. E.Torres, "Improved complete ensemble EMD:A suitable tool for biomedical signal processing", Biomedical Signal Processing and Control, vol. 14, pp: 19-29, 2014
[39] S. D. Muthukumaraswamy, "High-frequency brain activity and muscle artifacts in MEG/EEG: a review and recommendations", Front. Hum. Neurosci., vol. 7, 2013
[40] Andrea Mognon , Jorge Jovicich, Lorenzo Bruzzone, Marco Buiatti, " ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features", Psychophysiology, 2011,vol. 48, no. 2, pp: 229-240.
[41] Mammone N, La Foresta F, Morabito FC. Automatic artifact rejection from multichannel scalp EEG by wavelet ICA. IEEE Sensors Journal. 2012; 12(3):533–42.
[42] Gao J, Lin P, Yang Y, Wang P, Zheng C., " Real-time removal of ocular artifacts from EEG based on independent component analysis and manifold learning. ",Neural Comput Appl.Springer. 2010; 19(8):1217–26
[43] Jafarifarmand A, Badamchizadeh MA., " Artifacts removal in EEG signal using a new neural network enhanced adaptive filter", Neurocomputing. Elsevier. 2013.
[44] Guerrero-Mosquera C, Navia-Vazquez A. , "Automatic removal of ocular artifacts using adaptive filtering and independent component analysis for electroencephalogram data. IET signal Process. IET. 2012;Vol. 6 No.2,pp.:99–106.
[45] Rani BJA, Umamakeswari A., " Electroencephalogram-based brain controlled robotic wheelchair. Indian J Sci Technol. 2015;Vol. 8(S9),pp.188–97
[46] M. Zima, P. Tichavsk, K. Paul, andV. Krajˇca, "Robust removal of short-duration artifacts in long neonatal EEG recordings using wavelet-enhanced ICA and adaptive combining of tentative reconstructions," Physiological Measurement, vol. 33, no. 8, pp.N39–N49, 2012
[47] M. A. G. Correa and E. L. Leber, "Noise removal from EEG signals in polisomnographic records applying adaptive filters in cascade," in Adaptive Filtering Applications, L. Garcia, Ed., 2011
[48] P. Tichavsk´y and Z. Koldovsk´y, "Fast and accurate methods of independent component analysis: a survey," Kybernetika, vol. 47, no. 3, pp. 426–438, 2011
[49] A. K. Abdullah and Z. C. Zhu, "Blind source separation techniques based of brain computer interface system: a review," Research Journal of Applied Sciences, Engineering and Technology, vol. 7, pp. 484–494, 2014
[50] A. K. Abdullah, Z. C. Zhu, L. Siyao, and S.M. Hussein, "Blind source separation techniques based eye blinks rejection in EEG signals," Information Technology Journal, vol. 13, pp. 401–413,2014.
[51] S. Javidi, D. P. Mandic, C. C. Took, and A. Cichocki, "Kurtosisbased blind source extraction of complex non-circular signals with application in EEG artifact removal in real-time," Frontiers in Neuroscience, vol. 5, 2011
[52] X. Zhang, S. Qiu, Y. Ke et al., "Stimulus artifact removal of emg signals detected during functional electrical stimulation," Biomedical Engineering, 2013
[53] M. Li, Y. Cui, and J. Yang, "Automatic removal of ocular artifact from EEG with DWT and ICA Method," Applied Mathematics and Information Sciences, vol. 7, no. 2, pp. 809–816, 2013
[54] H. P. Huang, Y. H. Liu, C. P.Wang, andT. H. Huang, "Automatic artifact removal in EEG using independent component analysis and one-class classification strategy," Journal of Neuroscience and Neuroengineering, vol. 2, no. 2, pp. 73–78, 2013
[55] W.-Y. Hsu, C.-H. Lin, H.-J. Hsu, P.-H. Chen, and I.-R. Chen,"Wavelet-based envelope features with automatic EOG artifact removal: application to single-trial EEG data," Expert Systems with Applications, vol. 39, no. 3, pp. 2743–2749, 2012
[56] I. Daly, M. Billinger, R. Scherer, and G. M¨uller-Putz, "On the automated removal of artifacts related to head movement from the EEG," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 21, no. 3, pp. 427–434, 2013
[57] I.Winkler, S.Haufe, andM. Tangermann, "Automatic classification of artifactual ICA-components for artifact removal in EEG signals," Behavioral and Brain Functions, vol. 7, article 30, 2011
[58] X.-W.Wang,D.Nie, and B.-L. Lu, "Emotional state classification from EEG data using machine learning approach," Neurocomputing,vol. 129, pp. 94–106, 2014

[59] Y.-P. Lin, C.-H. Wang, T.-P. Jung et al., "EEG-based emotion recognition in music listening," IEEE Transactions on Biomedical Engineering, vol. 57, no. 7, pp. 1798–1806, 2010.

[60] D. P. Allen, E. L. Stegem¨oller, C. Zadikoff, J. M. Rosenow, and C.D. MacKinnon, Suppression of deep brain stimulation artifacts from the electroencephalogram by frequency domain Hampel filtering, Clin. Neurophys., vol. 121, 2010,pp. 1227 - 1232.

[61] M. T. Akhtar, W. Mitsuhashi, and C. J. James, "Employing spatially constrained ICA and wavelet denoising, for automatic removal of artifacts frommultichannel EEG data," Signal Process., vol. 92, no. 2, pp. 401–416,2012.

[62] G. Hosna and A. Erfanian, "A fully automatic ocular artifact suppression from EEG data using higher order statistics: Improved performance by wavelet analysis," Med. Eng. Phys., vol. 32, no. 7, pp. 720–729, 2010

[63] R. Mahajan and B. I. Morshed, "Sample entropy enhanced wavelet-ICA denoising technique for eye blink artifact removal from scalp EEG dataset," in Proc. 6th Int. IEEE/EMBS Conf. Neural Eng., 2013,pp. 1394–1397

[64] H. T. Gorji, H. Taheri, A. Koohpayezadeh, and J. Haddadnia, "Ocular artifact detection and removing from EEG bywavelet families: A comparative study," J. Inf. Eng. Appl., vol. 3, no. 13, pp. 39–47, 2013.

[65] H. Ghandeharion and A. Erfanian, "A fully automatic ocular artifact suppression from EEG data using higher order statistics: improved performance by wavelet analysis," Med. Eng. Phys., vol. 32, no. 7, pp. 720–729,2010.

[66] B. S. Raghavendra and D. N. Dutt, "Wavelet enhanced CCA for minimization of ocular and muscle artifacts in EEG," World Academy Sci.Eng. Technol., vol. 57, pp. 1027–1032, 2011

[67] C. Guerrero-Mosquera and A. Navia-Vazquez, "Automatic removal of ocular artefacts using adaptive filtering and independent component analysis for electroencephalogram data," IET Signal Processing, vol. 6, pp. 99-106, 2012

[68] M. B. Hamaneh, N. Chitravas, K. Kaiboriboon, S. D. Lhatoo, and K. A. Loparo, "Automated Removal of EKG Artifact From EEG Data Using Independent Component Analysis and Continuous Wavelet Transformation," IEEE Transactions on Biomedical Engineering, vol. 61, pp. 1634-1641, 2014.

[69] N. Mammone, F. L. Foresta, and F. C. Morabito, "Automatic Artifact Rejection From Multichannel Scalp EEG by Wavelet ICA," IEEE Sensors Journal, vol. 12, pp. 533-542, 2012.

[70] S. Khatun, R. Mahajan, and B. I. Morshed, "Comparative Study of Wavelet-Based Unsupervised Ocular Artifact Removal Techniques for Single-Channel EEG Data," IEEE Journal of Translational Engineering in Health and Medicine, vol. 4, pp. 1-8, 2016

[71] H. Nolan, R. Whelan, and R. B. Reilly, "FASTER: Fully Automated Statistical Thresholding for EEG artifact Rejection," Journal of Neuroscience Methods, vol. 192, pp. 152-162, 2010.

[72] D Puthank attil Subha & Paul K. J oseph & Rajen dra Acharya U& Choo Min Lim "EEG Signal Analys is: A Survey" J Med System springer,August 2010 ,pp. 195 –212.

[73] I. Daly, M. Billinger, R. Scherer, and G. M¨uller-Putz, "On the automated removal of artifacts related to head movement from the EEG," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 21, no. 3, pp. 427–434, 2013.

[74] I.Winkler, S.Haufe, andM. Tangermann, "Automatic classification of artifactual ICA-components for artifact removal in EEG signals," Behavioral and Brain Functions, vol. 7, article 30, 2011.

[75] X.-W.Wang,D.Nie, and B.-L. Lu, "Emotional state classification from EEG data using machine learning approach," Neurocomputing, vol. 129, pp. 94–106, 2014

[76] Y.-P. Lin, C.-H. Wang, T.-P. Jung et al., "EEG-based emotion recognition in music listening," IEEE Transactions on Biomedical Engineering, vol. 57, no. 7, pp. 1798–1806, 2010

[77] Nadia Mammone, Fabio La Foresta, Carlo Morabito, Automatic Artifact Rejection From Multichannel Scalp EEG by Wavelet ICA, IEEE SENSORS JOURNAL, VOL. 12, NO. 3 MARCH 2012

[78] Chaolin Teng, Yanyan Zhang, Gang Wang, The Removal of EMG Artifact from EEG Signals by the Multivariate Empirical Mode decomposition, 978-1-4799-5274-8/14/20l4 IEEE

[79] Ghandeharion,H.,andErfanian,A.(2010).Afullyautomaticocular artifact suppression from EEG data using higher order statistics: improved performancebywaveletanalysis. Med.Eng.Phys. 32,720–729.doi: 10.1016/j.medengphy.2010.04.010

[80] Gwin,J.T.,Gramann,K.,Makeig,S.,andFerris,D.P.(2010).Removal of movement artifact from high-density EEG recorded during walking and running. J.Neurophysiol. 103,3526–3534.doi:10.1152/jn.00105.2010

[81] Akhtar, Muhammad Tahir, Mitsuhashi, Wataru, & James, Christopher J. (2012). Employing spatially constrained ICA and wavelet denoising, for automatic removal of artifacts from multichannel EEG data. Signal Processing, Vol. 92,No.2,pp. 401-416

[82] Daly, I., Billinger, M., Scherer, R., & Muller-Putz, G. (2013). On the Automated Removal of Artifacts Related to Head Movement From the EEG. Neural Systems and Rehabilitation Engineering, IEEE Transactions on, Vol.21(3), pp.427-434.

[83] Fairley, Jacqueline, Georgoulas, George, Stylios, Chrysostomos, & Rye, David. (2010), " A Hybrid Approach for Artifact Detection in EEG Data. In K. Diamantaras, W. Duch & L. Iliadis (Eds.), Artificial Neural Networks – ICANN 2010 ,Vol. 6352, pp. 436-441: Springer Berlin Heidelberg.

[84] Gao, Junfeng, Lin, Pan, Yang, Yong, Wang, Pei, & Zheng, Chongxun.(2010), " Real-time removal of ocular artifacts from EEG based on independent component analysis and manifold learning. Neural Computing and Applications, Vol.19(8), pp.1217-1226.

[85] Jafarifarmand, Aysa, & Badamchizadeh, Mohammad Ali. (2013), "Artifacts removal in EEG signal using a new neural network enhanced adaptive filter. Neurocomputing, Vol. 103,pp. 222-231.

[86] Lawhern, Vernon, Hairston, W. David, McDowell, Kaleb, Westerfield, Marissa, & Robbins, Kay. (2012), "Detection and classification of subject-generated artifacts in EEG signals using autoregressive models. Journal of Neuroscience Methods, Vol.208,No.2, pp. 181-189.

[87] Lawhern, Vernon, Hairston, W. David, & Robbins, Kay. (2013a), "DETECT: A MATLAB Toolbox for Event Detection and Identification in Time Series, with Applications to Artifact Detection in EEG Signals. PLoS ONE, 8(4), e62944. doi:10.1371/journal.pone.0062944

[88] I. Daly, M. Billinger, R. Scherer, and G. M¨uller-Putz, "On the automated removal of artifacts related to head movement from the EEG," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 21, no. 3, pp. 427–434, 2013

[89] H. P. Huang, Y. H. Liu, C. P.Wang, andT. H. Huang, "Automatic artifact removal in EEG using independent component analysis and one-class classification strategy," Journal of Neuroscience and Neuroengineering, vol. 2, no. 2, pp. 73–78, 2013

[90] Ling Guo, D. Rivero, J. Dorado, Juan R.Rabunal, A. Pazos "Automatic epileptic seizure detection in EEG based on line length feature and artificial neural network" Journal of Neuroscience Methods, volume 191, issue 1, pp.101–109 (2010)

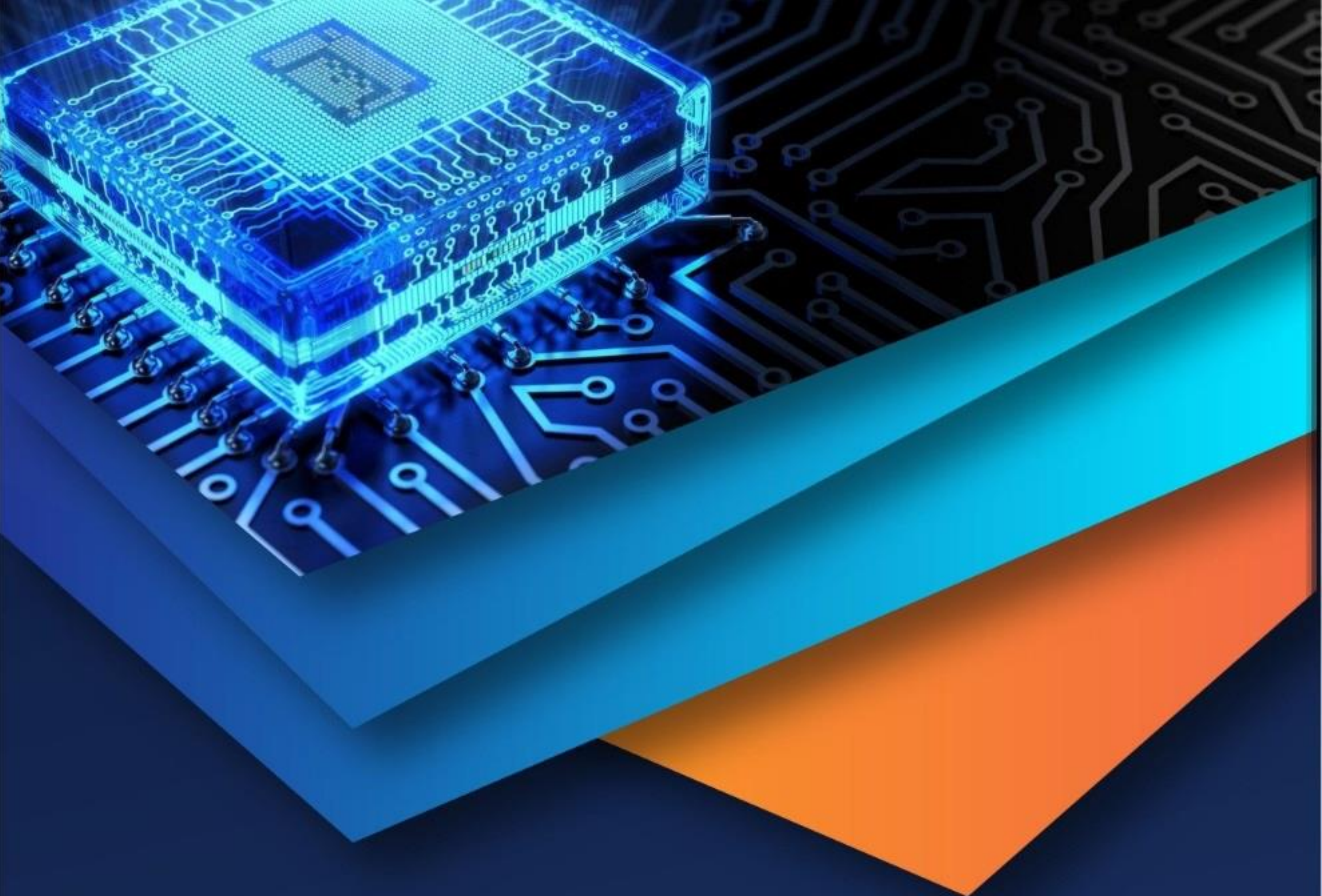
[91] Mingai Li, Yan Cui, Jinfu Yang,"Automatic Removal of Ocular Artifact from EEG with DWT and ICA Method" Applied Mathematics & Information Sciences. (2013), Appl. Math. Inf. Sci. 7, No. 2, pp.809-816

[92] Bertrand A, Mihajlovic V, Grundlehner B, Hoof CV, Moonen M.Motion artifact reduction in EEG recordings using multichan-nel contact impedance measurements. In: Proceedings of IEEEBiomedical Circuits and Systems Conference (BioCAS). 2013,pp. 258—61.

[93] Chi Zhang, Li Tong, Ying Zeng, Jingfang Jiang, Haibing Bu, Bin Yan, and Jianxin Li, "Automatic Artifact Removal from Electroencephalogram Data Based on A Priori Artifact Information",2015, BioMed Research International, Article ID 720450, pp.1-8

[94] Malik M.Naeem ,Mannan,MyungY.Jeong and MuhammadA.Kamran, "HybridICA—Regression:AutomaticIdentificationandRemovalofOcularArtifactsfromElectroencephalographicSignals" Frontiers in Human Neuroscience ,2014,Vol.10,Article193,pp.1-17

[95] ZhenYu Wang, Peng Xu, TieJun Liu, Yin Tian, Xu Lei, DeZhong Yao, " Robust removal of ocular artifacts by combining Independent Component Analysis and system identification" Biomedical Signal Processing and Control(Elsevier),2914,Vol. 10,pp. 250–25.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY