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Taxonomy on EEG Artifacts Removal Methods, Issues, and Healthcare Applications

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ABSTRACT

Electroencephalogram (EEG) signals are progressively growing data widely known as biomedical big data, which is applied in biomedical and healthcare research. The measurement and processing of EEG signal result in the probability of signal contamination through artifacts which can obstruct the important features and information quality existing in the signal. To diagnose the human neurological diseases like epilepsy, tumors, and problems associated with trauma, these artifacts must be properly pruned assuring that there is no loss of the main attributes of EEG signals. In this paper, the latest and updated information in terms of important key features are arranged and tabulated extensively by considering the 60 published technical research papers based on EEG artifact removal method. Moreover, the paper is a review vision about the works in the area of EEG applied to healthcare and summarizes the challenges, research gaps, and opportunities to improve the EEG big data artifacts removal more precisely.

KEYWORDS

Artifact Removal, DWT, EEG, EEMD, EMG, EOG, ICA

1. INTRODUCTION

The Big Data biological processes have very complex procedures, which imply neural as well as hormonal stimuli and responses. These biomedical signals generally represent a collective electrical signal attained from any organ, signifying a physical variable of interest. To store and handle these Big Data different technologies are frequently applied in the biomedical and health-care field (Luo & Zhao, 2016) to facilitate health-care activities. The energy management for real-time Big Data is a critical issue. Thus, energy and performance trade-off in resource optimized model design for Big Data is discussed in (E. Baccarelli & Stefa, 2016).

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The Biomedical Big Data cover a wide range of the following signal: electrooculogram (EOG), electroneurogram (ENG), electrogastrogram (EGG), phonocardiogram (PCG), carotid pulse (CP), vibromyogram(VMG), vibroarthogram(VAG), electrocardiogram (ECG), electroencephalogram (EEG), and electromyography (EMG). However, most widely used biomedical signals in healthcare applications are ECG, EEG, EMG, and EOG (Jiang & Lin, 2007), (Mowla & Paramesran, 2015).

The EEG signal is able to track changes within millisecond time-span, and is a good tool for analyzing brain activity (Urigüen & Zapirain, 2015). Moreover, this EEG signal is preferred to other signals. Certain physiological signal such as SET tracks changes in the blood circulation and positron emission (PET) measures the change in metabolism which is indirect indicators of electrical activity belonging to the brain, while EEG specifically tests the electrical activity of the brain. This software will assist in pre-processing (Roy & Shukla, 2019), (Bigdely & Robbins, 2016) of the EEG data to enable data sharing, archiving, large-scale machine learning/data mining and (meta-) analysis.

Usually, EEG Signals can be classified based on their frequency, amplitude and shape. The most common classification is based on the frequency of EEG signals (i.e. alpha, beta, theta, and delta) (Chen & Householder, 2018). Figure 1 shows the brain rhythms arranged according to increased frequencies. The brain waves with their frequency band and the corresponding brain activities are revealed in Table 1.

Table 1. Electroencephalography (EEG) Signal Frequency Bands.

Name	Frequency Band (Hz)	Predominantly Brain Activity
Delta	0.5 to 4	Sleeping
Theta	4 to 8	Dreaming, Meditation
Alpha	8 to 13	Relaxation
Beta	13 to 36	Alert/Working Problem Solving
Gamma	36 to 100	Multisensory semantic matching Perceptual function

Figure 1. Fundamental EEG Bands classification. (http://www.yalescientific.org/2013/12/the-brink-of-death-a-new-perspective/)

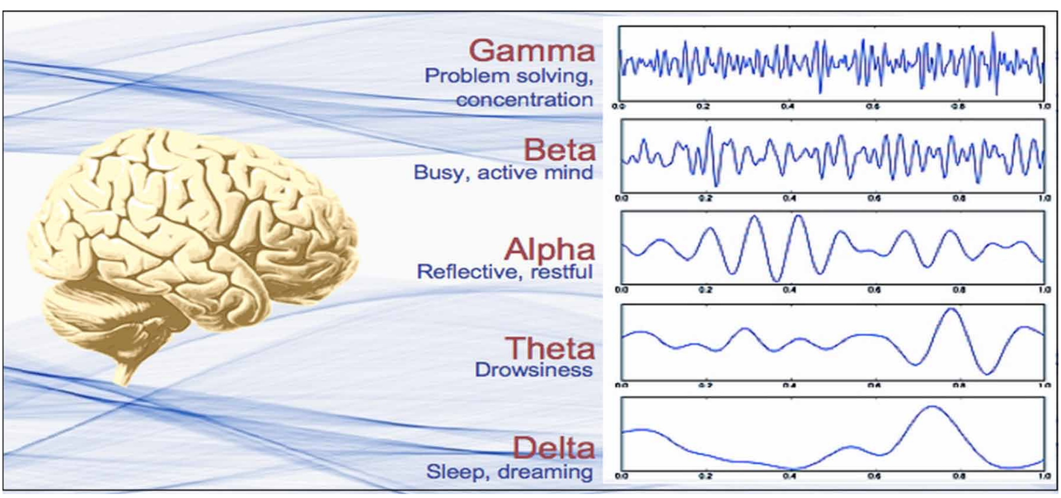
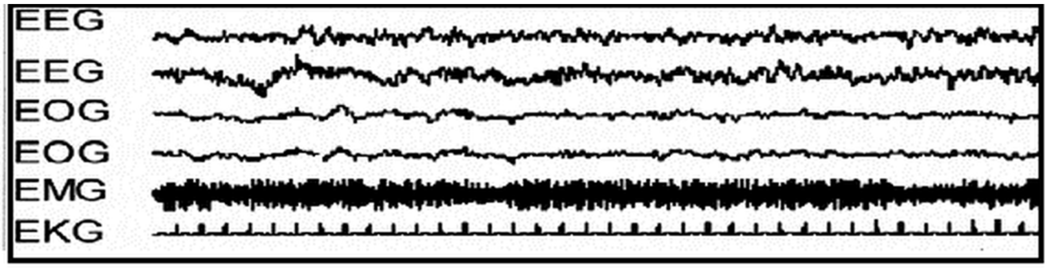


Figure 2. Superimposed recordings of the EOG, EEG, EMG, ECG (EKG)



Furthermore, EEG signals are highly sensitive to movement of the subject and noises being introduced externally likewise human head activation, eye movements, musculature, nearby electrical device interference. The movement in human body changes electrode conductivity or physicochemical reactions occurred at the electrode sites results in the artifacts. These artifacts can be categorized as muscle artifacts (EMG), glossokinetic artifacts, eye blink artifacts (EOG), eye movement artifacts, ECG artifacts, pulse artifacts, respiration artifacts, skin artifacts etc.

Figure 2 shows some of the artifacts who have the major influence on the quality and information of the data and therefore, leading to an erroneous form of signals. Therefore, it is required to identify and prune the artifacts from the desired signal for better analysis and diagnosis of human neurological diseases. In this review paper, around 200 research papers based on artifact removal techniques have been studied and state of the art analysis of about 60 research papers details are presented in a comparative tabular form. This information is useful to conclude and summarize the challenges and gaps present in Big EEG Data artifact removal field and opportunities needed to improve the quandary area.

Usually, the EEG epochs having the signal amplitude larger than selected threshold value have been rejected. This approach is stubborn and no adaption is allowed hence results in loss of meaning full information. Moreover, these artifacts will get overlapped with original EEG signal. Therefore, the threshold-based rejections will loss the important information. Thus, an automated component-based approach for artifact separation is required to solve this problem. The approach must transform the linear decomposition of signals into different source components. The components after decomposition will provide the information according to the different source types. Consequently, artifacts information is collected from separate sources and the final signal is reconstructed without these artifact sources to get artifact removed signal (Sweeney & Ward, 2013).

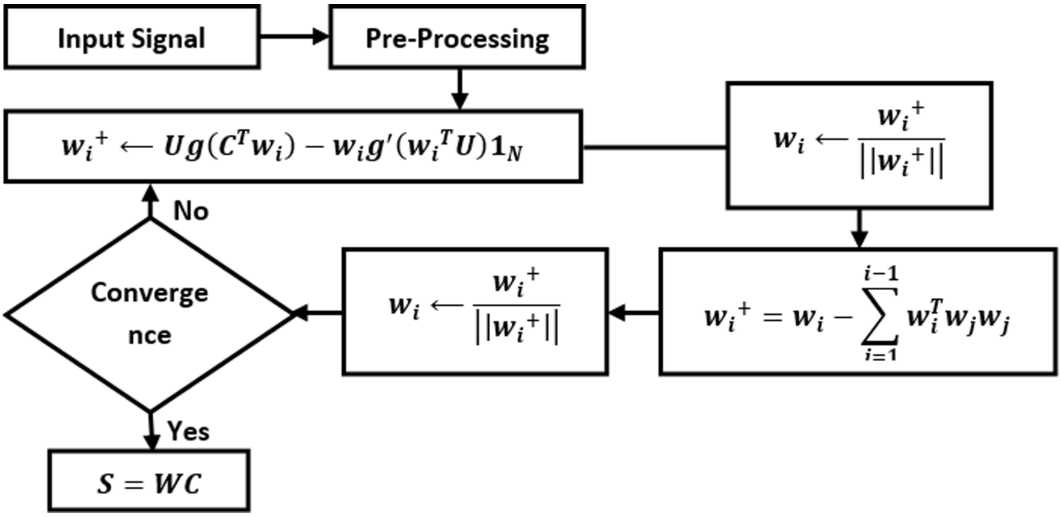
In general, the most frequently applied Big EEG Data artifact removal algorithms are:

- Blind Source Separations (ICA and CCA)
- EEMD
- Wavelet Transform (DWT and SWT)

The ephemeral information of these algorithms is discussed in next section.

The organization of this comprehensive review paper is as follows: section 2 overviews the existing artifact removal techniques employed for EEG artifact removal. In section 3, a comprehensive review of all the state-of-the-art EEG artifact removal-based research papers have been done. Various features from relevant artifact removal-based paper is compared in tabular form in section 4 and tables are attached as annexure. The summary prepared by the study of numerous research papers which are focused on specific artifact removal. Additionally, specific artifact removal methods are classified with our own experience in section 5. The conclusions are summed up with some recommendations in section 6. Some open issues related to artifact removal are also highlighted.

Figure 3. Independent component analysis algorithm flow-chart



2. BIG EEG DATA ARTIFACT REMOVAL TECHNIQUES

2.1. Blind Source Separation Algorithm

The Blind source separation is based on an unsubstantiated learning algorithm for estimating and separating the sources and artifacts components. Most frequently, Blind Source Separation can be done through Independent component analysis (ICA) (Kanoga & Mitsukura, 2015) and Canonical Correlation Analysis (CCA) (Soomro & Yusoff, 2014).

2.1.1. Independent Component Analysis (ICA)

The EEG signal separation into independent components requires ICA algorithm which uses the statistical and computational techniques. The ICA algorithm considers mixture signal $C = \left[c_1, c_2, c_j \ldots c_n\right]$ as input and generated independent sources $S = \left[s_1, s_2, s_j \ldots s_n\right]$ where W is the $n \times m$ mixing matrix:

$$S = WC \tag{1}$$

Figure 3 shows the flow of ICA algorithm. Here, w_i is column vector and w_i^+ is temporary variable, $g\left(.\right) and\, g'\left(.\right)$ represents first and the second derivate of nonlinear and non-quadratic functions. When the convergence is received w_{i+1} must be made orthogonal with respect to Equation 1 in order to differentiate the new components. Nevertheless, ICA algorithm is centered on higher order statistics and we cannot determine the order and variance of independent component. Therefore, second order statistics-based algorithm CCA is preferred for EEG artifact removal discussed in the next section.

2.1.2. Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) is first proposed by Hotelling. CCA is an algorithm for determination of the linear association between two set variables. This is done by using the data variance and co-variance matrix (Soomro & Yusoff, 2014).

The following are a number of linear combinations called A and B:

$$A_P = [a_{11}, a_{12}, \ldots..a_{1m}]^T \tag{2}$$

$$B_Q = [b_{11}, b_{12}, \ldots..b_{1n}]^T \tag{3}$$

Let C_{pp} and C_{qq} be the variance of the A_p and B_Q respectively and C_{pq} is the covariance between A_P and B_Q. Then the above equation can be rewritten as:

$$P^* = \frac{A_p^T C_{pp} B_Q}{\sqrt{A_p^T C_{pp} A_p} \sqrt{B_q^T C_{qq} B_q}} \tag{4}$$

To achieve the best of self correlations, this P^* should be maximum. Therefore, this optimization can be resolved by:

$$C_{pp}^{-1} C_{pq} C_{qq}^{-1} C_{qp} A_P = \rho A_P \tag{5}$$

$$C_{qq}^{-1} C_{qp} C_{pp}^{-1} C_{pq} B_Q = \rho B_Q \tag{6}$$

This ρ signifies the Eigen value which is identical to square of P^*:

$$\rho = \sqrt{P^*} \tag{7}$$

This canonical pair will be calculated and detached by calculating self-correlation and a mutual uncorrelation between sources input. Next subsection will discuss another effective EEG artifact removal algorithm namely Enhanced Empirical Mode Decomposition (EEMD).

2.2. Enhanced Empirical Mode Decomposition (EEMD)

Empirical mode decomposition algorithm is a non-linear way of representing a non-stationary signal into sum of zero-mean sections. This method disassembles a signal through an iterative method known as sifting in many intrinsic mode functions. The IMF1 function is the mean of the top and bottom enclosure of the original EEG signal, x(t). Then the residual signal is obtained by subtracting IMF1 from x(t). This cycle is iterated until the stop criterion is met (the remainder of the energy signal is near zero). The left residual signal is:

$$P_n\left(t\right) = P_{n-1}\left(t\right) - IMF_n\left(t\right) \tag{8}$$

where $P_n\left(t\right) = x\left(t\right)$.

Finally, the signal is reconstructed by adding all IMFs and residual signal as:

$$x(t) = P_n(t) + \sum_{i=1}^{N} IMF_i(t) \quad (9)$$

The detection method of IMFs is sensitive to unwanted signal components in the surrounding. Such noises affect the process of EMD. Mode mixing therefore is used in order to eliminate the disparate amplitude oscillations of almost all IMF peaks, which can be randomly available in the entire dataset. Consequence, the EMD algorithm version as Ensemble Empirical Mode Decomposition (EEMD) was introduced as more powerful and noise-assisted (Chen & Peng, 2014), which solves this mode of mixing dilemma and uses the average EMD ensembles which filter out IMFs for the signal provided. This method also depends on the noise level and amount of tests applied to the input signal. One another artifact removal approach is Wavelet Transform discussed briefly in the next section.

3. WAVELET TRANSFORM

The wavelet technique is used for more accurately filtering the corrupted signal. In the first stage, the mother wavelet should be selected and in the second step, the shape selection should be selected according to the source type. The signal is then subdivided into a variety of mother wavelet variants of time shifted and scaled version. Details and estimates were calculated at each level of the wavelet transformation. Then, artifact components are detected and removed by thresholds and finally other components are introduced to restore the refined signal without artifacts (Ghandeharion & Erfanian, 2010).

The most widely used transforming wavelet is Discrete Wavelet Transform. However, neural signal information is important when removing EEG artifacts. Some recent work therefore shows that SWT is a great tool to extract signal artifacts that retain neural knowledge of the original signal (Chang & Im, 2016).

Stationary Wavelet Transform (SWT), as no down sampling of the data is involved, is translation invariant (Ghandeharion & Erfanian, 2010). The invariance of translation is achieved by removing down-and-up DWT samplers. In addition, the coefficients of the filter were up sampled $2^{(j-1)}$ at the j^{th} level in the algorithm stage. In order to remove unpredictable motion artifact behavior from EEG signals, the SWT algorithm is preferred. The EEG signal is smooth over the duration as it includes all its important characteristics only.

These algorithms are frequently applied for available artifact suppression from EEG Big Data. Based on study and analysis of around 60 artifact removal research papers, the application frequency of artifact removal algorithms is summarized in Table 2. This extensive study is devoted to acquiring the best artifact removal algorithms for effective suppression of different artifacts from EEG signal.

Table 2 gives the recommendation that BSS-ICA algorithms are frequently applied artifacts suppression algorithm in single and two stages. However, this algorithm is based on higher order statistics and it results in complex and time-consuming approaches. Further, CCA algorithms are preferred over ICA due to simplicity (based on second order statistics). Moreover, EEMD algorithms are applied for single channel signal in order to convert single channel signal to multi-channel signals. The Wavelet Transform algorithms are also frequently applied both in single and two stages and some algorithm based on neural network and optimization algorithms are also applied for artifacts suppression. The state of art based on the type of artifact and applied artifacts removal algorithms is discussed in the next section.

Table 2. Frequency of artifact removal algorithms on electroencephalography (EEG)

Sr. No.	EEG Artifacts Removal Algorithms		Number of Stages	Application Frequency (Hz)
1.	Blind Source Separation	Independent Component Analysis (ICA)	Single Stage	11
			Two-stage	20
		Canonical Correlation Analysis (CCA)	Single Stage	04
			Two-stage	06
2.	Enhanced Empirical Mode Decomposition (EEMD)		Single Stage	04
			Two-stage	13
3.	Wavelet Transform (WT)		Single Stage	11
			Two-stage	15
4.	Others (Neural Network based)		Single and two stages	04

4. LITERATURE SURVEY

The most frequent EEG signal artifacts are EMG, EOG, and ECG. The state of the art is classified according to artifact types and their removal. The first review is emphasized on the research work done for removal of EOG and then focused on EMG artifact removal and as well as automatic detection and removal of artifacts have been reviewed and summarized.

Among all the artifacts EOG is the most dominant artifact. EOG artifacts are affecting the EEG signals at Frontal electrodes due to eye movements and eye blinks. These signals will spread throughout the scalp and contaminate the pure EEG signal. These artifacts are of high amplitude and low frequency in nature. As these EOG artifacts overlap spectrally to EEG signals, therefore it is very hard to eliminate by using conventional method (Jadhav & Naik, 2014). ICA-LMS (Least Mean Square) algorithm have applied by (Mosquera & Vázquez, 2010) and compared its performance with Recursive Least Squares (RLS) to eliminate EOG artifacts from EEG signal. In (Matiko & Tudor, 2013) more effective ICA algorithm has been used to eliminate the EOG and wavelet-based amplitude modulation features and support vector machine classifier is implemented to extract the features of the EEG. This method is complex and has large computational time.

The computational time for EOG artifact removal has been minimized by using the Short Time Fourier Transform (STFT) in (Huang & Fang, 2013) with less memory requirement. A wavelet transform-based adaptive filtering approach to eliminate rapid eye movement is proposed more accurately by (Betta & Menicucci, 2013). Further, Soomro et al. (Soomro & Jatoi, 2013), (Soomro & Malik, 2013) and (Soomro & Yusoff, 2014) have applied EEMD-CCA methodology to minimize the EOG artifact and compared their performance with EEMD-ICA approach of artifact removal and concluded that EEMD-CCA is more efficient with less computational time and much better signal artifact ratio (SAR) and correlation coefficient.

In (Bizopoulos & Fotiadis, 2013) research has been improved with artifact detection and removal of EOG artifacts. In this work, detection is based on Normalized Correlation Coefficient (NCC) and EOG artifact removal is done by using EEMD approach, though detection is not so accurate. The sample entropy enhanced Wavelet-ICA have suggested by (Mahajan & Morshed, 2013) for removal of EOG artifact and compared the performance with Zeroing-ICA and Wavelet ICA and proved better. Further, performance is improved by using improved multi-scale sample entropy and kurtosis with wavelet transform to recognize and eradicate the independent blink component (Mahajan & Morshed, 2015). To remove Ocular Artifacts more effectively in (Ge & Hong, 2014) the Fourth Order Tensor

Method (FOOBI) is applied and compared the performance with ICA and showed that FOOBI is better than ICA.

An automatic detection and suppression of ocular artifact is suggested by (Majmudar & Morshed, 2015) with DWT algorithm and compared its performance with SWT. The result shows that DWT processing time is 25 times faster than SWT for EOG artifact elimination. However, neural information is not preserved so well. Therefore, a real-time approach based on artificial intelligence (AI) to remove EOG artifacts has been employed by using Wavelet Neural Network algorithm (WNN). In the WNN algorithm, EOG behaviors have been learned first and then after training artifacts are removed accordingly. This approach is more computationally efficient in real-time application than ICA (Nguyen & Li, 2015). An improved approach with a combination of ICA and WNN is proposed by (Burger & Heever, 2015) to remove EOG from EEG signal. These detection algorithms are complex and have more computation time. A wavelet-based approach is proposed in (Zhao & Qiu, 2015) to remove EOG with CCA as well and proved better performance compared with ICA, CCA, and WICA.

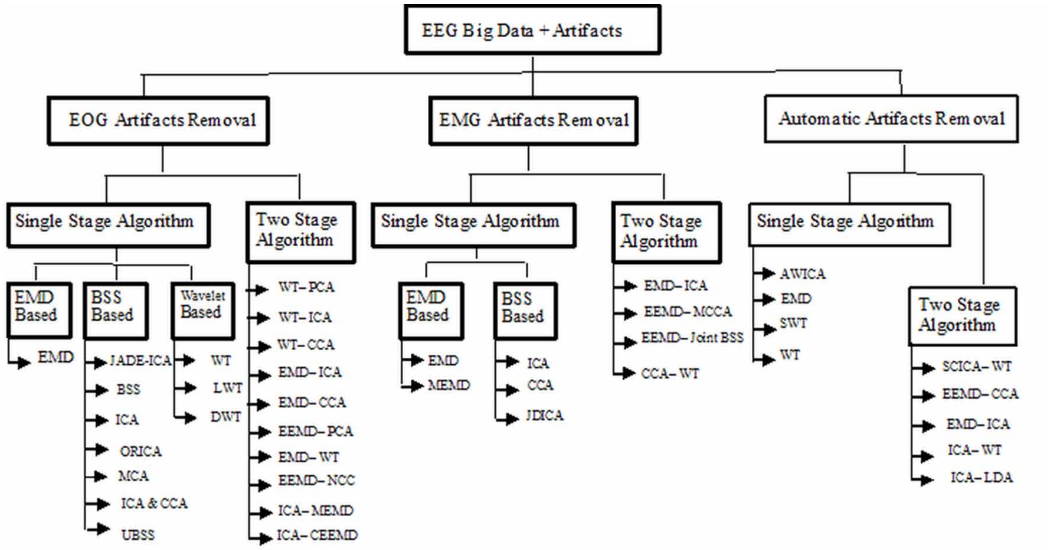
To reduce the complexity of the medical systems for healthcare, the single channel systems are preferred over multichannel systems. Therefore, Single channel EEG ocular artifact removal has been suggested by (Patel & Mariyappa, 2015) with EEMD-PCA approach and recommended this method for large input EEG data. The faster artifact removal algorithm termed as Complete EEMD (CEEMD) and ICA been proposed by (Kanoga & Mitsukura, 2015) to eliminate eye blink artifact from single channel EEG. Auxiliary, performance is compared and showed better than WICA, EMDICA and EEMDICA. Further, EOG artifact removal method based on Wavelet Transform (DWT and SWT) with the universal and statistical threshold have proposed by (Khatun & Morshed, 2015) and concluded that SWT with statistical threshold shows better performance than DWT for preserving the neural information of EEG while DWT with statistical threshold has fast execution time in comparison to another method.

Further, some research works have focused on adaptive artifact removal for EOG and EMG both, as in (Mowla & Paramesran, 2015). The artifacts are identified foremost with the classification and then EOG artifacts have been removed by Second Order Blind Identification (SOBI)-SWT and EMG artifacts filtered with CCA-SWT. This adaptive algorithm presented improved results in comparison to existing methods of artifact removal.

Recently EMG artifact removal has been focused by some researchers. The artifacts potential were generated due to the movement or contraction of muscles, swallow, walks and talks. The EMG artifacts are of wide spectral distribution than the signal generated in the human brain. Moreover, this EMG can be easily removed on the basis of duration and frequency. The performance of EMD, CCA, ICA and WT for EMG artifact removal have compared (Safieddine & Merlet, 2012) and concluded that for low SNR, EMD-ICA combination algorithm is effective and for high SNR, 2T-EMD or Contrast Maximisation 2 (CoM2) works better than other methods. Correspondingly DWT or CCA is preferred if numerical complexity is taken into account.

In addition, for EMG artifact removal (Teng & Wang, 2014) the multivariate-EMD method was compared to the ICA based approach by using SNR and MSE as parameter. However, (Chen & Ward, 2014) proposed EEMD-CCA and EEMD-IVA (Single Channel EEG data deletion EMG) and concluded that EEMD-CCA is outperformed by IVA. In addition, the EEMD-MCCA method is extended and the best results are shown (Chen & Peng, 2014). The EMG artifacts have suppressed in (Anastasiadou & Mitsis, 2014), (Anastasiadou & Mitsis, 2015) by CCA and CCA-WT methodology to remove EMG and applied, analyzed practically for patients with epilepsy. All the EEG artifacts removal-based research papers are compared in tabular form by considering some important key features and attached as the annexure.

Figure 4. Artifact removal based algorithms tree



5. ASSESSMENT TABLE

The numerous state-of-the-art research papers based on EEG artifact removal have been studied and summarized based on some features and tabulated as in Annexure section. The EEG Signal artifacts removal algorithm effectiveness are characterized by some evaluation metrics such as Efficiency, Feasibility, Complexity, Speed, Correlation Coefficient, Peak to Signal Noise Ratio (PSNR), Root Mean Square Error (RMSE), etc. All these evaluation metrics are compared and tabulated according to the research work done for specific artifact removal. Initially classification is focused on the progress of research work done for EOG artifact removal as tabulated in Annexure A and further classified for adaptive artifact removal as in Annexure B. The progress of the work for EMG artifact removal is presented in Annexure C. Annexure D contains the algorithms and their effectiveness evaluation for automatic artifact detection and removal. The study and analysis of these tabular comparisons suggest valuable conclusion which is discussed in subsequent section.

6. SUMMARY

In the healthcare system as the ambulatory device applications have increased, the EEG-based applications have been also increased accordingly. In real time applications, some unintended signals (i.e. artifacts) need to remove so as to improve the analysis and diagnosis of human neurological diseases for healthcare. Most undesired Big EEG Data artifact elements are EMG, EOG, ECG and motion artifacts. The taxonomy of artifacts removal algorithms according to artifacts are shown in Figure 4.

Figure 4 summarizes the various state of the art algorithms applied exclusively to remove the artifacts in the EEG signal. The algorithms are classified according to the artifacts types. It has been also analyzed from the above figure that two-stage algorithms are more effective to remove the artifacts than single stage algorithms. Moreover, the type of signal input is also an important aspect of analysis. If the signal is multichannel signal then ICA or Wavelet Transform based algorithms are applied to suppress the artifacts, however, if EEG signal is single channel then EMD based approaches

Table 3. Artifact removal algorithms applied according to the artifact type

Type of Artifact	Artifact Removal Algorithms
Electrooculogram (EOG)	1. BSS (PCA, ICA, CCA) is frequently applied as single stage approach 2. WT-BSS is applicable for multichannel input two-stage approaches 3. EEMD-BSS is applicable for single channel input two-stage approaches 4. Two-stage approaches present most effective EOG artifact suppression
Electromyogram (EMG)	1. EEMD and BSS are applied for Single stage approaches 2. EEMD-BSS are applied for single channel two-stage approach 3. CCA-WT is applied for multi-channel two-stage approach 4. After BSS approaches SWT algorithm application presents most effective EMG artifact suppression
Automatic Artifact detection and Removal	1. EMD, ICA, SWT algorithms are applied as single stage approaches 2. EEMD-BSS are applied for single channel two-stage approach 3. BSS-WT are applied for multi-channel two-stage approach 4. Neuro-Fuzzy and optimization algorithm also applied

are applied initially to convert single channel signal to multichannel and then BSS or WT based approaches have been applied to eliminate the artifacts more effectively.

The major cause of EMG artifacts is due to frontalis and temporal muscles. In the classical work (Mijovic & Huffel, 2010) EEMD-ICA method have applied to remove the muscle artifact; however, this muscle artifact removal process was improved by (Chen & Ward, 2014) through EEMD-CCA algorithm. This EEMD-CCA algorithm is compared and proved better than the performance of EEMD-ICA. Further, in (Chen & Peng, 2014) EEMD–MCCA is applied to improve the EMG artifact removal by increasing PSNR and reducing the RMSE values in comparison to the existing muscle artifact removal methodologies available. The algorithm CCA-WT has implemented by (Anastasiadou & Mitsis, 2015) to attain best correlation coefficients for removal of EMG artifacts.

The most corrupting artifact in EEG signal is Electrooculogram (EOG), generated due to eyelid movement and eye blinking. The Haar wavelet-based ICA method is applied in (Mahajan & Morshed, 2013) to suppress EOG artifacts and used entropy as a statistical measure. Further, in (Mahajan & Morshed, 2015) an automatic EOG artifact detection with WICA has been employed and statistical measure is considered as modified multi-scale entropy. To compare the performance the ROC curve is plotted which shows significant improvement in sensitivity and specificity. The complexity and computational time of artifact removal algorithm are reduced by CCA method in (Soomro & Yusoff, 2014) and compared with an existing ICA method to remove EOG artifacts. Further, (Mowla & Paramesran, 2015) have implemented SOBI-SWT to improve the EOG artifact removal performance.

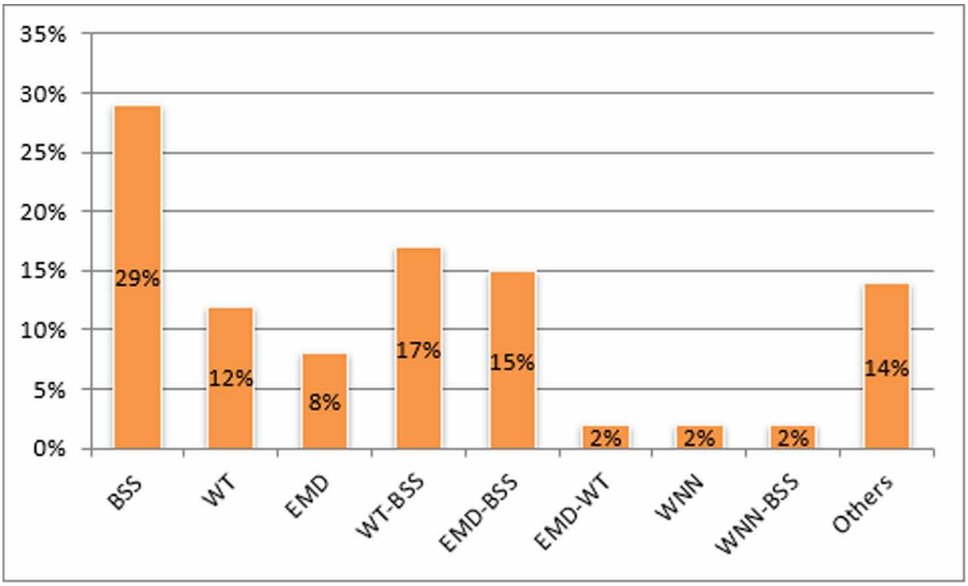
The automatic detection and correction of artifact algorithm have been employed by (Chuang & Lin, 2014) with the independent component ensemble to remove eye blink, EOG, EMG adaptively. Further, (Radüntz & Meffert, 2015) have used ICA-LDA algorithm as an automatic, reliable, real-time capable and practical tool for automatic detection and correction of artifacts from EEG signal.

Above study and investigation summarize that the particular artifact removal algorithms are effective according to the type of input artifacts whose information is recapitulated in Table 3.

Table 3 suggests that BSS algorithms are most effective for EOG artifact removal; CCA-WT is most effective for EMG artifact suppression.

PSNR, RMSE, Correlation coefficient, and complexity are the key factors for any artifact removal methods. This artifact removal can be done by using some efficient techniques as CCA, ICA, DWT, SWT, EEMD etc. These methodologies are faster, reliable and accurate for separation of different artifacts (EOG, EMG, ECG etc.) from the input EEG signal. These artifact removal methods can be applied to either single channel or multiple channel input EEG signal. This input EEG signal can be of different recording duration and also can be of different sampling rate and data. Some artifact

Figure 5. The State-of-the-Art algorithms applied for Artifact Removal in Percentage



removal methods are feasible with some applied conditions as SNR values, a number of channels, type of diseases, etc.

Commencing the study of the published technical and review articles of EEG artifact removal, it can be summarized that the high PSNR value resemblance to the better EEG signal quality and least RMSE value indicates improved artifact separation. The improved correlation coefficient (Teng & Wang, 2014) indicates that improved identification and separation of artifacts from the input noisy EEG signal can be attained those results in better source separation. The complexity and quality of artifact removal techniques can be affected by the speed and accuracy factors of the algorithm. The complexity of the methodology is varied according to the employed artifact removal methods and their computational time. The computational time of ICA is much higher than CCA, EEMD, DWT algorithms for artifact removal. Furthermore, minimum computational time is taken by DWT (Safieddine & Merlet, 2012). The computational time and complexity will affect the execution speed of artifact removal methods. Therefore, the improved computational time will diminish the execution speed of the algorithm. Thus, these all key features will suggest the adaptability of artifact removal algorithms according to the input and types of artifact. Moreover, Figure 5 shows a graphical representation of percentage artifact removal methodologies employed in literature for EEG signal only.

The review and summary of the research papers state that almost 29% research papers used BSS algorithm as effective artifact removal technique, among them 47% focused on removal of EOG, 18% applied the BSS algorithm to remove EMG, 6% deals with ECG and 12% automated the algorithm for artifact removal. Further, 12% used WT algorithm, 8% applied EMD algorithm, 15% applied cascading of EMD and BSS algorithm, 17% WT and BSS algorithm combination, 2% used the combination of EMD and WT approach, and remaining 4% algorithm used an automated approach for artifact removal.

The various artifact removal methodologies as discussed above are of mere importance and very helpful in healthcare for diagnosis of neurological disease such as epilepsy, tumour, sleep apnea, etc. Research is still going on for the improvement of artifact removal of EEG which will definitely lead to the better diagnosis and treatment of neurological disorders.

7. CONCLUSION

On the basis of the extensive study of the above-mentioned research papers, it is concluded that the artifact removal methods are an imperative pre-processing step for Big EEG Data signals. This cleaned EEG signal will support more accurate diagnosis and analysis of neurological diseases in the medical field. In literature, research work is basically focused on removal of EOG, EMG and motion artifact. The comprehensive review work is categorized according to the removal methodologies employed for various artifacts in the EEG signals.

Most frequently applied artifact removal algorithms in literature are EEMD, DWT, SWT, ICA, CCA and sometimes combinations of these methodologies. These methods have been compared based on some performance evaluation parameters as PSNR, RMSE, and correlation coefficient, etc. and proved the effective results using simulations. Finally, according to study and analysis of these research papers, it can be concluded that Blind Source Separation techniques are the most widely employed algorithms to remove the EOG artifacts from EEG signals. As these BSS algorithms are based on source separation and once artifact source is identified then their removal will be easier. Moreover, EMG artifacts available in EEG signal are better suppressed by wavelet transform. These Wavelet Transform algorithms will smooth out the EMG artifacts broad spectrum randomness available in the EEG signal while preserving the neural information. The Review analysis of above-mentioned research papers concludes that cascading of different artifact removal algorithms can be more optimal for eliminating various artifacts from EEG signal. Therefore, processing of the signal will improve the quality of the signal, which will be helpful in analysis and diagnosis of neurological diseases in health care.

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APPENDIX A

Table 4. Feature comparison table for EOG artifact removal

	Authors Name and feature comparison of their paper					
Sequence Number	**1**	**2**	**3**	**4**	**5**	**6**
Authors \ Features	(Vigon & Fernandes, 2000)	(Salwani & Jasmy, 2005)	(Ghandeharion& Erfanian, 2006)	(Vazquez & Maquin, 2007)	(Romero & Barbanoj, 2008)	(Kiamini & Ahmadi, 2009)
Used techniques	JADE-ICA	lwt	wT-ica	wd-ica	BSS	EMD-WT
Artifact removed	EOG	EOG	EOG	EOG	EOG	EOG
Year	2000	2005	2006	2007	2008	2009
PSNR (dB)	>50	High	Satisfactory	20	40	20
RMSE (μV)	Low	Low	0.3	0.0453[a], 0.3040[b]	1.35	2.20E-01
Feasible	If SNR above 50	with Haar computation	With Thresholding	Yes	Good with AMUSE and SOBI	Yes
Efficiency/ Reliable	Yes	High	96.4%	Efficient with SURE algorithm	Reliable	Highly Efficient
Complexity	Medium	Least	Complex	Complex	Medium	Less
Speed	Low	Very high	Low	Low	Medium	High
Data Duration	10 s	10 s	4 s	8 s	3 min	2s
Sampling rate (Hz)	125	256	256	256	100	250
Sample data	1250	2560	-	-	-	500
Channel	32	10-20 system	10-20 system	4	10-20 system	64
Average Correlation coefficient	0.99 (JADE), 0.98 (ICA)	Satisfactory	0.1579[a], 0.1776[b]	.7698[a], .7076[b]	Good	High

LWT- Lifting Wavelet Transform
Number of channels-*, First Subject - a, Second Subject -b

APPENDIX B

Table 5. Feature comparison table for EOG artifact removal continued

	Authors Name and feature comparison of their paper					
Sequence Number	**7**	**8**	**9**	**10**	**11**	**12**
Authors \ Features	(Kumar & Vimal, 2009)	(Mosquera &Vázquez, 2010)	(Ghandeharion& Erfanian, 2010)	(Babu & Prasad, 2011)	(Zhao & Qiu, 2015)	(Nguyen & Li, 2015)
Used techniques	wt	ica	ICA-WT	PCA-WT	CCA-WT	WNN
Artifact removed	EOG	EOG	EOG	EOG	EOG	EOG
Year	2009	2010	2010	2011	2015	2015
PSNR (dB)	Good	0.8	High	19.1103	14.5699	_
RMSE (μV)	Low	0.35	0.025	7.45E-09	Low	19.2154
Feasible	Yes	Fair	Yes	Low	Needs Little signal alteration	Yes
Efficiency/ Reliable	Improved Quality	Effective Denoising	97.8%	Comparable high	Better than ICA CCA and wICA	Accurate than Wavelet Thresholding
Complexity	Least	Complex	Complex	Medium	Moderate	Medium
Speed	High	Low	High	Medium	Medium	Low
Data Duration	10 s	10 s	60 s	400ms	4 s	30 s
Sampling rate (Hz)	128	200	256	128	250	128
Sample data	-	2000	-	15000	1000	3840
Channel	4	10-20 system	10-20 system	2	32	32
Average Correlation coefficient	0.68	0.9945	Medium	-	0.97	0.9

WNN- Wavelet Neural Network

APPENDIX C

Table 6. Feature comparison table for EOG artifact removal continued

	Authors Name and feature comparison of their paper					
Sequence Number	**13**	**14**	**15**	**16**	**17**	**18**
Authors \ Features	(Hsu & Chen, 2012)	(Soomro & Malik, 2013)	(Soomro & Jatoi, 2013)	(Huang & Fang, 2013)	(Bizopoulos& Fotiadis, 2013)	(Matiko & Tudor, 2013)
Used techniques	ica-dwt	Emd-cca	emd-ica	ORICA	NCC-EEMD	MCA
Artifact removed	eog	EOG	EOG	EOG	Eog	EOG
Year	2012	2013	2013	2013	2013	2013
PSNR (dB)	Good	6.0[a]/2.2[b]	1.04761	Good	7.649	Sufficient High
RMSE (μV)	Low	Min	Low	Low	0.215	Low
Feasible	Yes	Suitable for Online Removal	Not Feasible	Yes	Satisfactory	Yes
Efficiency/ Reliable	84.4%	Efficient if electrode placed distant	Effective Denoising	Satisfactory	Satisfactory	Reliable
Complexity	Complex	Medium	Highly Complex	Complex	Less	Less
Speed	Low	Medium	Least	Least	High	High
Data Duration	20 s	500 ms	800ms	25 s	4 s	4s
Sampling rate (Hz)	256	250	250	128	1000	256
Sample data	-	1000	200	-	250	1024
Channel	5	2	2	7	10-20 system	1
Average Correlation coefficient	High	0.908808[a]/0.864514[b]	0.871094	0.9135	0.767	0.94

ORICA- Online Recursive ICA, NCC- Normalized Cross Correlation, MCA- Minor Component Analysis
Number of channels-*, First Subject - a, Second Subject -b

APPENDIX D

Table 7. Feature comparison table for EOG artifact removal continued

	Authors Name and feature comparison of their paper					
Sequence Number	**19**	**20**	**21**	**22**	**23**	**24**
Authors \ Features	(Mourad & Niazy, 2013)	(Mahajan & Morshed, 2013)	(Betta & Menicucci, 2013)	(Mahajan & Morshed, 2015)	(Zhao & Peng, 2014)	(Turnip, 2014)
Used techniques	EMD	WT-ICA	WT	ICA-DWT	DWT-APF	JADE-ica
Artifact removed	EOG	EOG	EOG	EOG	EOG	Eog
Year	2013	2013	2013	2014	2014	2014
PSNR (dB)	High	Satisfactory	High	High	Low	3.590[a], 5.393[b]
RMSE (μV)	Medium	Low	0.0002	0.89	0.6443	Low
Feasible	Yes	Fair	Yes	Low no. of channels	Yes	Yes
Efficiency/ Reliable	Effective for Single Channel	94%	Effective and Reliable	Effective Denoising	Fast prediction speed, low nMSE	Effective
Complexity	Less	Complex	Least	Complex	Medium	Complex
Speed	High	Low	Very high	Low	Medium	Low
Data Duration	20 s	30 s	25 s	78 s	80s	80 s
Sampling rate (Hz)	250	128	500	128	256	128
Sample data	4100	-	-	5120	5120	-
Channel	10-20 electrode System	14	10-20 system	10-20 system	10-20 system	6
Average Correlation coefficient	0.79	0.6704	Good	0.7771	High	Good

APF- Adaptive Predictor Filter
First Subject - a, Second Subject -b

APPENDIX E

Table 8. Feature Comparison Table for EOG Artifact Removal Continued

Authors Name and feature comparison of their paper						
Sequence Number	**25**	**26**	**27**	**28**	**29**	**30**
Authors \ Features	(Soomro& Yusoff, 2014)	(Ge & Hong, 2014)	(Wang & Yan, 2015)	(Majmudar & Morshed, 2015)	(Lyzhko & Siniatchkin, 2015)	(Kanoga & Mitsukura, 2015)
Used techniques	cca & Ica	UBSS	MEMD-ICA	DWT	ica	ceemd-ica
Artifact removed	EOG	EOG	EOG	EOG	eog	eog
Year	2014	2014	2015	2015	2015	2015
P*SNR* (dB)	7.6891[a],6.5274[b], -3.5709[c]	Good	High	Good	High	11.86±3.60
RMSE (μV)	Low	Low	22	Low	0.1569	Low
Feasible	High	Yes	Yes	Yes	Fair	Yes
Efficiency/ Reliability	Reliable algorithm	Effective	Efficient	Effective	Good	11.86±3.60%
Complexity	High complex	Less	Complex	Least	Complex	High
Speed	Least	High	Low	Very High	Low	Least
Data Duration	10 s	10s	3-8 s	35 s	100 ms	60 s
Sampling rate (Hz)	256	256	500	256	5000	256
Sample data	2560	2560	-	128	-	-
Channel number	18	16	10-20 system	1	64	15
Average correlation coefficient	.5739[a],.8229[b], .8427[c]	0.9963±0.0060	(.789/.165)[a], (.747/.186)[b], (.795/.15)[c]	(.304*/.303^)[a], (.297*/.299^)[b], (.506*/.603^)[c]	0.91	High

UBSS- Undetermined Blind Source Separation, MEMD- Multivariate EMD, CEEMD- Complete EEMD
First Subject- a, Second Subject- b, Third Subject-c

APPENDIX F

Table 9. Feature Comparison Table for EOG artifact removal continued

Authors Name and feature comparison of their paper				
Sequence Number	31	32	33	34
Authors \ Features	(Patel & Mariyappa, 2015)	(Chang & Im, 2016)	(Burger & Heever, 2015)	(Khatun & Morshed, 2015)
Used techniques	EEMD-PCA	MSDW	Wnn-ica	WT
Artifact removed	EOG	EOG	eog	eog
Year	2015	2015	2015	2015
P*SNR* (dB)	-18	Good	Good	-
RMSE (μV)	0.31± 0.12	0.1536 ± .1321	5.3731	Min with Swt-st
Feasible	With EOG only	Yes	Yes	Good for single channel
Efficiency/ Reliability	92%	Good	Efficient with minimum loss	Efficient with dwt-st
Complexity	Moderate	Low	Highly complex	Least
Speed	Medium	High	Least	Least
Data Duration	25 s	15 s	10s	105 s
Sampling rate (Hz)	1000	2048	1000	128
Sample data	5000	-	-	5000
Channel number	64	1	128	14
Average correlation coefficient	Satisfactory	0.1893 ± 0.735,	0.99, 0.92	0.41± 0.21

MSDW- Maximum Sliding Window

APPENDIX G

Table 10. Feature Comparison Table for EOG, EMG and ECG Artifact Removal

Authors Name and feature comparison of their paper						
Sequence Number	**1**	**2**	**3**	**4**	**5**	**6**
Authors \ Features	(Jadhav & Naik, 2014)	(Hu & She, 2015)	(Mowla & Paramesran, 2015)	(Jiang & Lin, 2007)	(Grouiller& David, 2007)	(Mahadevan & Mugler, 2008)
Used techniques	dwt	ANFIS, FLNN	cca-swt, sobi-swt	WT	ica	Hermite basis function
Artifact removed	emg & eog	EOG & EMG	EOG & EMG	ECG	bcf	bcg
Year	2014	2015	2015	2007	2007	2008
P*SNR* (dB)	Medium	23.18 (EOG), 21.34 (EMG)	-19 (EOG), -7.5 (EMG)	5.64	2	0.9
RMSE (μV)	Low	0.6335 (EOG), 0.7853 (EMG)	Low	Low	Medium	0.1531
Feasible	Yes	Only with EOG, EMG	For EOG and EMG	Yes	No	Fair
Efficiency/ Reliability	Acceptable	High Extraction Efficiency	Efficient than BSS-SCD	97.5%	Not Optimal	Efficient
Complexity	Least	Less	Less	Least	Complex	Less
Speed	High	High	High	Very High	Low	High
Data Duration	10 s	6 s	4 s	4-5 min	180 s	3500 ms
Sampling rate (Hz)	256	50	256	200	1024	1000
Sample data	-	6000	-	-	8000	-
Channel number	10-20 system	10-20 system	55	10-20 system	20	32
Average correlation coefficient	0.7574	0.701 (EOG), 0.0633 (EMG)	.999 (EOG), 1.00 (Emg)	0.6138	0.8	Satisfactory

ANFIS: Adaptive Neuro-Fuzzy Inference System, FLNN – Functional Link Neural Network

APPENDIX H

Table 11. Feature comparison table for EMG artifact removal

Authors Name and feature comparison of their paper						
Sequence Number	**1**	**2**	**3**	**4**	**5**	**6**
Authors \ Features	(Mijovic & Huffel, 2010)	(Sweeney & Onaral, 2012)	(Safieddine& Merlet, 2012)	(Korhonen & Sarvas, 2011)	(Chen & Peng, 2014)	(Teng & Wang, 2014)
Used techniques	eemd-ica	Eemd-ica	ICA, CCA, EMD, WT	ica	eemD-Multi-set cca	memd
Artifact removed	Muscle Artifacts	Motion Artifacts	EMG	Muscle Artifacts	emg	emg
Year	2010	2012	2012	2013	2014	2014
P*SNR* (dB)	Good	14.82	-	Satisfactory	4.4	Good
RMSE (μV)	0.6479	Low	min with 2T EMD	Min	0.19	0.9572
Feasible	Yes	Yes	ICA for high SNR and 2T-EMD for low SNR	Yes	Yes	Yes
Efficiency/ Reliability	Highly Efficient	For Motion Artifact only	Good at -30dB, average at -25 dB, less efficient at 20dB to -5 dB	Good	Effective	Efficient
Complexity	Highly Complex	Highly Complex	ICA High complex	Complex	Medium	Less
Speed	Least	Medium	DWT High speed	High	Medium	High
Data Duration	10 s	9 min	8 s	-	10s	8 s
Sampling rate (Hz)	250	200	256	1450	1000	200
Sample data	-	500	2048	-	10000	1600
Channel number	21	2	32	60	1	6
Average correlation coefficient	Satisfactory	0.765	-	Satisfactory	0.99	Good

APPENDIX I

Table 12. Feature comparison table for EMG artifact removal continued

Authors Name and feature comparison of their paper				
Sequence Number	**7**	**8**	**9**	**10**
Authors \ Features	(Anastasiadou & Mitsis, 2014)	(Chen & Ward, 2014)	(Anastasiadou & Mitsis, 2015)	(Sardouie & Merlet, 2015)
Used techniques	cca	eemd-Joint-bss	Cca-wt	jdica
Artifact removed	Muscle Artifacts	emg	EMG	emg
Year	2014	2014	2015	2015
P*SNR* (dB)	Good	3	-5 for (1*), -10for (14*), -15 for(15*),-20 in (18*)	High
RMSE (µV)	(.8349^/.1374*)[a], (.2423^/.1807*)[b], (.1023^/.0546*)[c]	0.2	0.8665(1*), 0.8981(14*), 0.9790(15*), 0.8755(18*)	Minimum with JDICA
Feasible	Fair	0.98	Yes	Good with less no of electrodes
Efficiency/ Reliability	Satisfactory	Efficient	Efficient	Best to Paediatric Patient
Complexity	Less	Medium	Medium	Complex
Speed	High	Medium	Low	High
Data Duration	30 m	10s	5 min	20s
Sampling rate (Hz)	200	250	200	256
Sample data	-	-	3000	5120
Channel number	10-20 system	21	10-20 system	12
Average correlation coefficient	.869[a]/.562[b]/.486[c]	Good	0.9508	Satisfactory

JDICA- Jacobi-like Deflationary ICA, First Subject- a, Second Subject- b, Third subject-c, Channel fp1-*, channel fp2- ^.

APPENDIX J

Table 13. Feature comparison table for automatic artifact detection and removal

Authors Name and feature comparison of their paper						
Sequence Number	**1**	**2**	**3**	**4**	**5**	**6**
Authors \ Features	(Mammone& Morabito, 2012)	(Akhtar & James, 2012)	(Sweeney & Ward, 2013)	(Mert & Akan, 2013)	(Islam & Yang, 2014)	(Chuang & Lin, 2014)
Used techniques	AWICA	scica-wT	eemd-cca	emd	SWT	ICA-EMD
Artifact removed	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal
Year	2012	2012	2013	2013	2014	2014
P*SNR* (dB)	Satisfactory	Satisfactory	8.21	27.34	Max 17.6 (at 25 dB)	Satisfactory
RMSE (µV)	$(.13^c/.12^d)^1$, $(.12^c/.15^d)^2$, $(.05^c/.05^d)^3$, $(.09^a/.1^b)^4$	-35.264^a, -31.331^b	Low	Medium	Min .02 (at 5 dB)	0.19
Feasible	Fair	No	Yes	No	Yes	Yes
Efficiency/ Reliability	Effective Artifact Suppression	Inconsistent	Fairly efficient than ICA and WT	High Efficient	80%	84%
Complexity	Moderate	Complex	Moderate	Less	Least	High Complex
Speed	Low	Low	Medium	High	Least	Low
Data Duration	5 s	20 s	20s	5 s	100 s	1s
Sampling rate (Hz)	128	200	200	200	200	500
Sample data	512	4000	-	100	-	-
Channel number	8	6	2	1	16	10-20 system
Average correlation coefficient	$(0.62^c/0.68^d)^1$, $(0.71^c/0.6^d)^2$, $(0.95^c/0.95^d)^3$, $(0\ .81^a/0.8^b)^4$	-	High	Satisfactory	-	0.95075

a-CH1, b-CH2, c-CH3, d-CH4, 1-electrical trend, 2- linear shift, 3- muscle, 4- eye blink, Number of channels-*,

APPENDIX K

Table 14. Feature comparison table for automatic artifact detection and removal continued

Authors Name and feature comparison of their paper				
Sequence Number	**7**	**8**	**9**	**10**
Authors \ Features	(Priyadharsini & Rajan, 2014)	(Daly & Putz, 2015)	(Radüntz & Meffert, 2015)	(Islam & Yang, 2015)
Used techniques	ANFIS-PSO*	ICA-WT	ICA-LDA	Wt
Artifact removed	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal	Automatic Artifact Detection and Removal
Year	2014	2015	2015	2015
P*SNR* (dB)	(0.0781/15.0245)[a], (1.0294/21.8553)[b]	Satisfactory	Satisfactory	High
RMSE (μV)	(5.1424e-004)[a], (5.8904e-004)[b]	0.0107 ± 0.017[1], 0.1035 ± 0.0629[2], 0.0081 ± 0.007[3], $0.0001\pm.00003$[4], 0.0036 ± 0.0073[5]	Low	0.64
Feasible	Yes	Yes	Fair	Yes
Efficiency/ Reliability	Efficient than ANFIS	Efficient	87.7%	Efficiency Improved
Complexity	Less	Complex	Complex	Least
Speed	High	Low	Low	Very High
Data Duration	4 s	4 s	94.34 s	5 min
Sampling rate (Hz)	256	512	500	256
Sample data	1000	-	-	-
Channel number	10-20 system		25	32
Average correlation coefficient	Good		Satisfactory	0.9891

a-CH1, b-CH2, 1-Blink artifact, 2- Movement artifact, 3- Moving artifact, 4- Failing electrode, 5-Slow EOG electrode

* ANFSI PSO-Adaptive Neuro-Fuzzy Inference System-Particle Swarm Optimization, LDA- Linear Discriminant Analysis

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