Artifacts and Noise Removal for Electroencephalogram (EEG) : A Literature Review

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***Abstract*—Electroencephalogram (EEG) is a signal collected from the human brain to study and analyze the brain activities. However, raw EEG may be contaminated with unwanted components such as noises and artifacts caused by power source, environment, eye blinks, heart rate and muscle movements, which are unavoidable. These unwanted components will effect the analysis of EEG and provide inaccurate information. Therefore, researchers have proposed all kind of approaches to eliminate unwanted noises and artifacts from EEG. In this paper, a literature review is carried out to study the works that have been done for noise and artifact removal from year 2010 up to the present. It is found that conventional approaches include ICA, wavelet based analysis, statistical analysis and others. However, the existing ways of artifacts removal cannot eliminate certain noise and will cause information lost by directly discard the contaminated components. From the study, it is shown that combination of conventional with other methods is popularly used, as it is able to improve the removal of artifacts. The current trend of artifacts removal makes use of machine learning to provide an automated solution with higher efficiency.**

***Index Terms*—EEG, noise, artifact**

I. INTRODUCTION

The raw EEG may contain contaminated elements known as the artifacts. General artifacts include electrocardiography (ECG), ocular artifacts (EOG) and muscle activity (EMG). ECG is provoked by heart beats [1], where EOG induced by eye blinks or low frequency pattern that caused by eye movements [2] [3], and EMG is caused by the movements of the jaws, tongue, head or body. EOG and EMG activities are obligatory in EEG recordings [2] [3] [4]. In addition, during the recording of EEG, there may be noises from the power adapter and the environment. The present of these unwanted components in the EEG will result in inaccurate analysis. Over the years, researchers have developed several methods to remove the artifact and noise efficiently. In this paper, a literature review has been done on approaches for noise and artifact removal on EEG. This paper is divided into six sections. In Section I, an introduction is given about this paper. In Section II, methods that implemented independent component analysis (ICA) to remove artifact and noise will be discussed. Section III explains about statistical analysis methods used for artifacts and noises removal, followed by the wavelet based analysis in Section IV. Section V discusses about other stand alone artifact and noise removal approaches. Section VI will provide a summary and conclusion of the literature review.

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II. INDEPENDENT COMPONENT ANALYSIS

One of the most used approaches to remove artifacts is by utilizing the Independent Component Analysis (ICA) [5]. ICA is a multivariate analysis that decomposes the original signals into a brand-new set of linear signals, which is known as the independent components (ICs). ICA enables the identification of the artifacts in the given brain signal. Generally, the identification of artifacts using ICA can be divided into three steps. Firstly, the signal will be decomposed into ICs by using ICA. Next, stand-alone ICs which are varied from each other will be identified, and these ICs are often discarded from

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the signal manually. Subsequently, the remaining ICs will be concatenated to form an artifact-free signal.The formula of ICA is given as:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \tag{1}$$

Where **A** is an unknown matrix called the mixing matrix and **x**(t), **s**(t) are the two vectors representing the observed signals and source signals respectively. The goal of ICA is to recover the original signals, **s**(t) from only the observed signal **x**(t). The estimate for the sources is obtained by first identifying the unmixing matrix **W**, where $\mathbf{W} = \mathbf{A}^{-1}$. The estimate $\hat{\mathbf{s}}$(t) of the independent sources is obtained by:

$$\hat{\mathbf{s}}(t) = \mathbf{W}\mathbf{x}(t) \tag{2}$$

There are existing softwares such as Brainstorm [6] and EEGlab [7] which can detect the artifacts using the method described above and remove them. These softwares are commonly used including the works by Kang et al. [8] and Miraglia et al. [9]. These softwares can automatically detect the artifact and remove them by users' control. However, the direct discard of the signal may cause information lost. Therefore, there are several methods that are developed to future improve the conventional ICA-based artifacts removal approach.

Yin et al. [10] proposed a method which makes use of ICA, factor analysis (FA) and multivariate empirical mode decomposition (MEMD), targeting to remove unwanted power of additive noise in the EEG signals. In their work, FA is combined with a standard ICA algorithms, which is the joint approximate diagonalization of eigenmatrices (JADE) [11]. There are two types of noises appearing in the signal, which are the additive noise generated from each sensor, and common component noises. The approach of implementing ICA to separate unwanted components from the signals is unable to remove the additive noise, and therefore FA are initially used to reduce the power of additive noises. FA and standard principal component analysis (PCA) both are able to rank the principle components in signal decorrelation. However, in comparison with the PCA, FA consider the noise variance in the analysis. Therefore, FA approach allows the reduction of high level additive noise. To remove common component noises, ICA is used to perform the independent source decomposition and discard the noise components. However it was shown that some high-frequency noisy components cannot be removed by using only FA and ICA. Therefore, MEMD is further used to recompose the signal into a finite set of amplitude-frequency modulated components, named as intrinsic mode functions (IMFs). The high frequency scales of IMF components is able to reflect the noises, the desired components can be isolated. From their experimental result, it was shown that the resultant clean signal is almost similar to the ideal case.

On the other hand, Corradino et al. [12] proposed a method which makes use of ICA with regression. Their method is able to prevent information lost, as a control feedback scheme is used to check the residual artifacts content and recognized the one that significantly represents artifacts. The proposed method uses ICA as the first gate to decomposed the signal into independent components (ICs) and check for ICs that are artifactual. Subsequently, mathematical regression is used to compute the relationship coefficient between the detected ICs that recognized as artifacts and the original signal to enable confirmation of artifacts elements to correctly remove them without inform ational lost. Their approach is shown to be effective, as the cleaned ICs was shown to be a comparable frequency components contributes in all bands.

In the research work of Zamm et al. [13] that implements wireless EEG measurements, the EEG signal is filtered using a Hanning window FIR filter as a preparation for application of ICA. In their process of removing artifacts, CORRMAP EEG Lab plug-in written by Filipa Campos Viola [14] is used. However, it is found that the removal of artifact detected by ICA often causes the raw EEG signal to be distorted. Therefore, to overcome this problem, Gauba et al. [15] have applied moving average filter (MA) to smooth the signal by simply replaces each data value with the average neighboring values after the employment of ICA. After applying MA filter, the original signal was shown to be smoothed. The moving average is calculated using the formula:

$$\bar{y}\,[i] = \frac{1}{M}\sum_{j=0}^{M-1} x[i+j] \tag{3}$$

where $\bar{y}\,[i]$ is the output signal, *x* is the input signal and *M* is the number of points used in their average calculation.

III. STATISTICAL ANALYSIS METHOD

Researchers also makes use of statistical method to investigate the EEG for artifacts removal. Statistical analysis involved in exploring unknown pattern or trend in a set of given data. The pattern that defines the artifacts will become a reference to separate and discard the artifacts from the signal. Many approaches has been done to improve the artifacts removing efficiency using statistical analysis, which includes combination of other algorithm.

Nolan et al. [16] proposed a statistical method known as Fully Automated Statistical Thresholding (FASTER) for EEG artifacts rejection. Firstly, the channels are analyzed for artifacts by calculating the variance, mean correlation and Hurst exponent. Any contaminated channels will be interpolated. Next, the data are then epoached from -500ms to 1500ms, and baseline corrected from -200ms to 0ms. Epochs is then analyzed for artifacts by computing the mean for the amplitude range, variance and channel deviation. Any detected artifacts will be discarded. Subsequently, ICA is applied to find the independent components. To further remove artifacts in the independent components, correlation, spatial kurtosis, slope in filter band, Hurst exponent and median gradient will be computed from the independent components. The ICs which are found to be artifacts will be removed from the datasets. Next, each channel in the epochs is analyzed in term of variance, median gradient amplitude range and channel deviation.

Each contaminated channel will be interpolated in between all the channels. Finally, the event related potential for each step mentioned above is taken, baseline corrected from -200ms to 0ms, and subsequently concatenated to make a grand average dataset. Amplitude range, variance, channel deviation and max EOG value are computed from the grand average dataset to screen for artifacts at the final stage. Based on the experiment results, it was shown that FASTER has more than 90% of sensitivity and specificity for detecting contaminated channels, EMG and eye movement artifacts, white noise and linear trends. In addition, FASTER has more than 60% sensitivity for recognizing contaminated epochs.

On the other hand, an implementation of Riemannian geometry proposed by Barachant et al. [17] is able to detect for multi variation in the signals caused by artifacts. The input signal is described in term of covariance matrices as the detection is based on Riemannian geometry. This approach allows the spatial structure of artifacts to be accounted because artifacts are sensitive to the correlation structure of EEG channels. The main idea is to estimate a reference covariance matrix computed from the signal. Riemannian distance is calculated if its too far, it will be rejected.

The Riemannian distance, d_R between the covariance matrix $\mathbf{P}_1$ and $\mathbf{P}_2$ can be computed by using:

$$d_R(\mathbf{P}_1, \mathbf{P}_2) = \| \log_{10} \mathbf{P}_1^{-1} \mathbf{P}_2 \|_F = [\sum_{i=1}^{n} \log_{10}^2 \lambda_i]^{\frac{1}{2}} \qquad (4)$$

where λ_i are the real strictly positive eigenvalues of $\mathbf{P}_1^{-1}\mathbf{P}_2$ and $\|.\|_F$ is the Frobenius norm of a matrix. In their experiment, they compute the classification by using filtered and unfiltered signal. It was shown that the filtered signal presents lower classification error rates.

To remove simultaneous ocular and muscle artifact, Chen et al. [18] proposed a method which employs independent vector analysis (IVA) to jointly employed higher-order statistic (HOS) and second order statistic (SOS) simultaneously. The IVA is an extended version of ICA from one to multiple data sets. It uses criteria related to information theory to separate each data set into mutually independent sources, at the same time utilizing dependence correlation between data sets to make the corresponding sources across data sets dependent with each other. In combination of IVA, HOS and SOS, IVA makes use of HOS to ensure statistical independence of the source. Meanwhile, when the multiple data sets are time-delayed from the multichannel recordings, IVA applies SOS to explore temporal structure information of potential sources. IVA combines the advantages of both SOS and HOS, which isolate ocular and muscle artifacts from the EEG. Their experiment was carried out using stimulated data and real EEG data. Both of the results show that their method presents good signal and noise ratio (SNR) value.

Tavildar et al. [19] proposed an application of multivariate empirical mode decomposition (MEMD) and canonical correlation analysis for EEG motion artifact removal. In their method, MEMD decomposes the data into its almost orthogonal constituents known as intrinsic mode function (IMF) and is used to find common oscillatory modes of the signal within multivariate data. The MEMD decompose the signal into four sets of IMFs corresponding to the EEG signal and three accelerometers. Subsequently, Canonical Correlation Analysis (CCA) is used to find the correlation between the IMFs of the EEG signal and IMFs of accelerometer signal. The IMFs of EEG signal which have large mutual correlations with the IMFs of the accelerometer signal are selected as the artifacts IMFs and will be removed. In comparison with existing motion artifacts removal method on the same dataset, it was shown that their method present an increase of 16 % of artifact removal efficiency.

IV. WAVELET BASE ANALYSIS

Other than the approaches mentioned above, there are also plenty of researchers which implemented wavelet transform to separate artifacts from EEG signals. Conventionally, wavelet transform will firstly decomposed EEG signals into wavelet components, which ease the detection of artifacts. After the identification of wavelet components that contain artifacts, they will be discard from the signal. The remaining wavelet components will be used to reconstruct a clean signal. However, the general way of removing artifacts using wavelet transform might cause information lost and faulty reconstruction of clean signals. There are plenty of work done that combines the wavelet transform with other methods, to further improve general method.

Mammone et al. [20] proposed a method which is known as Automatic Wavelet Independent Component Analysis (AW-ICA) for an automatic artifacts rejection from multichannel scalp EEG. Firstly, the input EEG will be decomposed using the Discrete Wavelet Transform (DWT) to partition each channel of the original data set into four major bands of the brain activity. Each rhythm of each channel is represented by a Wavelet Component (WC). Each of the WCs will be channelled to ICA analysis to concentrate the artifacts into a few ICs. The resulting artifactual Wavelet Independent Components (WICs) are automatically detected and removed. Subsequently, the reconstruction of the clean signal involves two steps, which are inverse ICA and inverse Discrete Wavelet Transform (DWT).

In the removal of artifact in EEG, wavelet often being used with ICA [21]. Al-Qazzaz et al. [22] apply ICA and wavelet to remove artifact in EEG of normal and demented patients. Their approach firstly determine the ICs, which are artifacts. The artifact ICs will be marked as critical and denoised through DWT and rebuild the corrected ICs to obtain artifact-free EEG. Their proposed method is compared to two other approaches which are based on ICA and wavelet transform (WT) using cross-relation and peak signal to noise ration (PSNR). The proposed method outperformed in the comparison.

The similar approach which uses ICA with wavelet can also be seen in work of Sai et al. [23]. Their method manage to overcome the inconvenient of visual inspection or arbitrary threshold by using a classifier to identify eye blink artifacts in EEG. In conjunction with the usage of ICA with wavelet, Jirayucharoensak et al. [24] elaborated the ICs with lifting wavelet transform (LWT) in order to extract useful neural signals from the artifact ICs. ICA-LWT is able to be used in real-time applications as it does not require complex computation. The implementation of ICA with wavelet can also be seen in work of Hamaneh et al. [25]. Their method uses continuous wavelet transform (CWT) to create the ICs. They detect for peaks and checks if they occur periodically. ICs that meet the criteria of being an artifact will be rejected.

A second-order blind identification (SOBI) based ICA is implemented using wavelet thresholding in the work of Kaur et al [26]. Artifact related ICs are detected using SOBI ICA, followed by wavelet thresholding. Wavelet thresholding is implemented based on soft thresholding to the coefficients retrieved by DWT to seperate the artifact ICs with any other activities. The artifact signals will be removed from the EEG. To evaluate the efficiency of the proposed method, the parameters of root mean square error (RMSE) and PSNR are calculated. It shows that their approach provides a better suppression of artifacts.

An unsupervised eye blink artifact removal with modified multiscale sample entropy (mMSE), kurtosis and wavelet-ICA is proposed by Mahajan et al. [27]. After the decomposition of ICA, mMSE is computed for all the ICs. Normal distribution is used to detect the artifact. ICs with mMSE lower than the threshold will be marked for wavelet correction. The ICs computed will undergo the same process for Kurtosis. Finally, the marked ICs will be denoised using biorthogonal wavelets. Inverse DWT will be used to reconstruct the signal after denoising process. The method achieves 90% of sensitivity with average specificity of 98% compared with conventional ICA-wavelet based approach.

Another unsupervised artifact removal is brought up by Khatun et al. [28]. To obtain wavelet coefficient that is artifact related, DWT and stationary wavelet transform (SWT) are used. To denoise the wavelet coefficients, thresholding is applied over the detail coefficients. To evaluate the performance of their method, correlation coefficient (CC) is used. CC is a statistical method that shows the degree of association between two variables. By comparing the resultant signal with clean signal, their method presents the highest CC, which shows that the approach can effectively remove the artifacts.

Other than ICA, wavelet can also be used with together with notch filter, as presented in the work of Tibdewal et al. [29]. Conventional filtering cannot wipe off ocular artifact (OA) as EEG and artifacts have overlapping spectra. In their method, an adaptive thresholding of wavelet coefficients is used to remove frequent OA and IIR notch filter of 50Hz to remove power line interference. By using visual inspection, the time domain plots of the resultant signal show that the amplitude is stepped down and intact with the cerebral activity. The power spectral density plot of the signal also presents power reduction for low frequency components and maintain the high frequency components. Their method is shown effective on reducing artifacts and noise, while preserving the cerebral activity.

Another filtering approach using wavelet can be seen in the work of Chen et al. [30]. DWT is applied to the input signal to reconstruct rough OAs approximation. Subsequently, Kalman filter is used to optimize the OAs approximation, followed by the subtraction of optimized OA. For performance evaluation, mean squared error (MSE) is calculated for their approach as well as other method for comparison. Comparing to ICA, DWT, Adaptive Noise Cancellation (ANC) and Wavelet Packet Transform (WPT), their method present the lowest MSE, which achieved satisfying result.

V. OTHER ARTIFACTS REMOVAL APPROACHES

Besides from the approaches mentioned above which make use of ICA, statistical method and wavelets, there are plenty of standalone method which are very innovative and efficient. In conjunction, Jas et al. [31] proposed an automated artifacts rejection for EEG data which capitalizes on cross-validation to estimate the optimal peak-to-peak threshold, which is a commonly used quantity to identify bad trials in EEG. The approach is then further extended to a more sophisticated algorithm that estimates this threshold for yielding trial-wise bad sensors. By referring to the bad sensors, the trial is subsequently repaired by either interpolation or discarded. Their method is evaluate by computing MNE value and visual inspection, by comparing to baseline condition without rejections and several artifact rejection method. It was shown that the propose algorithm presents the best result.

In the implementation of EEG signal in predicting traumatic brain injury (TBI) patient using qualitative EEG, Mikola et al. [32] proposed a method to discard the general artifacts such as eye blinks and heart beat in the signal. Input EEG signals are divided into 6 hours epochs overlapping by 1 hour. Furthermore, each of the epoch is divided into 1-minute segments and divided into 5 seconds windows overlapping by 4 seconds. As the EEG signals is analyzed in the form of spectral power, the windows that contain signal powers that exceed empirically determined threshold will be discarded.

Moreover, Fisher et al. [33] found that physiological artifacts such as heartbeat, respiration as well as line noise are best eliminated by doing cross-referencing one hemisphere to the other. As example, in the usage of 10-20 system, channel 2 to 3, Cc to Ci. In making use of the electrode channel, Li et al. [34] adds on external EOG and EKG channel which is able to monitor eye and cardiac artifact. Therefore, in order to extract a clean EEG signal, both of the EOG and EKG are removed.

Congedo et al. [35] implemented two inhibition filters that consistently monitor the EMG and EOG activity during all the neurofeedback sessions. Once the EMG or EOG signal exceeded its threshold, the corresponding inhibit filters will be triggered and interrupted the feedback loop. The loop will be resumed one second subsequently if the inhibit filters are inactive.

Besides the implementation of inhibition filters, Torse et al. [36] proposed an adaptive filtering method to filter out the artifacts. Normalized Stochastic Least Mean Square (NLMS) adaptive algorithm has been designed in their work due to its stability and suitability with non-stationary signals. When ECGs and EOGs are channel and sum up in the adaptive filter arrangement, it is used to generate a clean EEG signal.

On the other hand, artifacts cannot always be identified on the basis of just one or two features of the EEG signal extracted using amplitude and power statistics. Therefore, Dhindsa et al. [37] proposed a filter-bank artifact rejection for single-channel artifact detection for EEG using machine learning method which can determine appropriate set of features which define the best mapping from time series segments to artifacts identification. Their method uses supervise machine learning to detect for the presence of an artifact, which require labeling the training data to train the model. In order to label the data, EEG expert checked and labeled the data as common data or artifacts. The labeled data are next used to train the model and form the artifacts bank, which subsequently used to classify the input EEG signals. By comparing the method to FASTER and EEGlab artifact detection methods, the area under the receiver operating characteristic (ROC) curve and classification result (false negative rate (FNR) and false positive rate (FPR)) using the cleaned signal are evaluated. The proposed method outperformed among the methods.

Mohammadpour et al. [38] proposed a method which makes use of a hidden Markov model-based approach to remove EEG artifact. Hidden Markov Model (HMM) is a finite stochastic state machine which can predict probability distribution of observing a sequence. In their method, HMM is used to detect the eye blink artifacts and removed them from the signal. To train the HMM, the input signals are decomposed into overlapping window using DWT, followed by applying Hanning window for windowing purpose. Next, the signal sequence is break into informatics statistical feature by using standard deviation and feed to the HMM.

Gavas et al. [39] proposed a method which remove artifact from EEG signals using low resolution Emotiv Device. Emotiv provides Application Programming Interface (APIs) as part of their Software Development Kit (SDK) to detect the eye-blink regions. However, their experimental results show that by applying only the SDK does not present acceptable accuracy. Hence, they proposed a methodology for a robust detection of eye-blinks. Once the eye-blinks are detected, a high pass filtering is performed to filter out the eye-blinks to output a clean EEG signal.

VI. Summary

In order to analyze the EEG without any interruption of noises and artifact, researchers proposed several approaches to eliminate the artifact in order to obtain a clean EEG signals. Generally, the methods that are used include ICA, statistical analysis, wavelet based and other more. However, many works that have been done to further improve the efficiency and sensitivity of the conventional way in removing artifacts. Table I presents a summary of approaches that have been done.

A clean EEG allows analysis to be done more effectively without mislead by unwanted elements. ICA is used regularly in artifacts removal due to its capability of separating signals into individual components. Artifacts can be removed easily by analyzing the independent components (ICs) which deviate from the others. There are plenty of plug-ins that are developed for instant artifacts removal. However, discarding the artifacts ICs might cause information lost and unable to remove certain noise. Therefore, researchers combine other methods together with ICA, targeting to improve the efficiency of removing the artifacts, at the same time preserve the information in the input EEG. From Table I, it can be seen that ICA is combined with statistical analysis, FA and MA. Rather than just discard the contaminated ICs, method such as interpolation is shown to be able useful in preventing information lost while removing the artifacts.

Other than that, Table I also shows that wavelet-based approaches are often combined with ICA and statistical analysis. The main reason is ICA and statistical analysis are both useful in discriminating the contaminated components after the decomposition of signal using wavelet transform. Another option which is shown to be effective is by combing filtering with ICA. As conventional filtering is unable to remove frequent artifacts and noise, researches applied adaptive filtering. Experimental results have proven that the utilization of adaptive filtering is effective in removing the contaminated components while preserving cerebral activities information in the signal.

In utilization of statistical analysis, the signal is often empirically analyzed and decomposed into components using functions. The popularly used method is MEMD. MEMD is shown to be effective in improving the artifacts removal efficiency experimentally.

Other than the ICA, wavelet and statistical approach, there are stand alone methods to remove artifacts and noises. Table I shows that the recent trend of artifacts removal is machine learning based approach. Artifacts cannot always be identified based on only one or two features extracted using amplitude and power statistic. Therefore, to further improve artifacts removal, huge datasets of features containing artifacts to developed an informative classifier which can classify the signal's components. One of the work is the development of filter bank. Other than amplitude and power based features, there are work done that employed statistical features in the training of classifier.

Conventionally, artifacts removal are carried out manually using visual inspection. To further improve the accuracy of inspection, method such as ICA are used to identified artifacts components. However, the process is time and human power consuming. Therefore in the current trend of artifacts removal, it can be seen that machine learning based approaches are introduced. The objective is to provide an automated solution which can enable artifacts to be removed in higher time and accuracy efficiency.

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TABLE I
SUMMARY OF ARTIFACTS REMOVAL APPROACHES

Author\ year	ICA	Statistical Analysis	Wavelet	Other	Notes
Nolan et al. [16], 2010	✓	✓			Proposed FASTER algorithm 60% of detection sensitivity.
Yin et al. [10], 2012	✓			✓	Make use of FA, MEMD and ICA to remove unwanted power of additive noise.
Mammone et al. [20], 2012	✓		✓		AWICA is proposed for an automatic artifacts rejection from multichannel scalp EEG. ICA is used with DWT to computed WICs.
Barachant et al. [17], 2013		✓			Riemannian geometry is used. Resultant signal presents lower classification error rates compared to the original signal.
Congedo et al. [35], 2013				✓	Implemented two inhibition filters that consistently monitor the EMG and EOG activity.
Jirayucharoensak et al. [24], 2013	✓		✓		ICA is used with LWT to extract useful neural signals from the artifact ICs. ICA-LWT can be used in real-time applications as it does not require complex computation
Hamaneh et al. [25], 2014	✓		✓		Peaks is checked using CWT and ICA. ICs that meet the criteria of being an artifact will be rejected.
Corradino et al. [12], 2015	✓	✓			ICA is combined with regression. The cleaned ICs is presented as comparable frequency components contributes in all bands.
Kaur et al [26], 2015	✓		✓		SOBI based ICA is implemented using wavelet thresholding. The parameters of RMSE and PSNR are calculated. The approach provides a better suppression of artifacts.
Mahajan et al. [27], 2015	✓	✓	✓		mMSE, kurtosis and wavelet-ICA are used. The method achieves 90% of sensitivity with average specificity of 98% compared with conventional ICA-wavelet artifact based approach.
Mikola et al. [32], 2015				✓	Time windows that contain signal powers that exceed empirically determined threshold will be discarded.
Li et al. [34], 2015				✓	By using external channel (EKG, EOG), the artifacts are detected and removed.
Tavildar et al. [19], 2016		✓			MEMD and canonical correlation analysis are used for EEG motion artifact removal.The method present an increase of 16% of efficiency.
Torse et al. [36], 2016				✓	NLMS adaptive algorithm has been designed due to its stability and suitability with non-stationary signals.
Gavas et al. [39],2016				✓	Remove artifact low resolution Emotiv Device. Eye blinks are removed using high pass filter once detected by the device.
Fisher et al. [33], 2016				✓	By cross-referencing electrodes of one hemisphere to the other, physiological artifacts can be removed.
Khatun et al. [28], 2016			✓		DWT and SWT are used to obtain wavelet coefficients. Thresholding is applied over the detail coefficients to denoise them. By comparing the resultant signal with clean signal, their method presents the highest CC.
Tibdewal et al. [29], 2016			✓	✓	Adaptive thresholding of wavelet coefficients is used to remove frequent OA and IIR notch filter of 50Hz to remove power line interference. The proposed method is shown effective on reducing artifacts and noise, while preserving the cerebral activity.
Chen et al. [30], 2016			✓	✓	Kalman filter is used, followed by the subtraction of optimized OA. MSE is calculated for evaluation. The method present the lowest MSE.
Jas et al. [31], 2017				✓	Applied cross-validation to estimate the optimal peak-to-peak threshold. By computing MNE value and visual inspection, it was shown that the propose algorithm presents the best result.
Al-Qazzaz et al. [22], 2017	✓		✓		Compared to two ICA and WT based approaches using cross-relation and PSNR. The proposed method outperformed.
Sai et al. [23], 2017	✓		✓		Overcome the inconvenient of visual inspection or arbitrary threshold by using a classifier. artifacts.
Dhindsa et al. [37], 2017				✓	A filter-bank based artifacts removal approach. By comparing the method to FASTER and EEGlab artifact detection methods, the area under the ROC curve and classification result (FNR and FPR) using the cleaned signal are evaluated. The proposed method outperformed among the methods.
Chen et al. [18], 2017		✓			Employ IVA to jointly employed HOS and SOS simultaneously. Both of the results show that their method presents good SNR value.
Mohammadpour et al. [38], 2017				✓	HMM machine learning method is used to remove eye blinks artifacts.
Zamm et al. [13], 2017	✓				Make use of ICA remover plug-in from EEG lab.
Gauba et al. [15],2017	✓			✓	ICA is combined with MA. The resultant signal is shown to be smoothed.