A Review on Preprocessing of EEG Signal

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***Abstract*—Electroencephalogram (EEG) is the documentation of brain's electrical activity tapped from the scalp. The signals picked from the scalp do not express an accurate representation of the brain signals. These bio-signals need to be processed in order to be used for the desired application. To unravel this problem, there is a necessity to define a strong and repeatable EEG pre-processing method. EEG data pre-processing specifies a procedure of remodeling the raw EEG data into a clean EEG data by removing the undesirable noise and artifacts thereby converting it into suitable format for further analysis and interpretable by the user. This paper tends to review various EEG preprocessing techniques that has been described within the published literatures so as to focus on the acceptable preprocessing modality for a specific application.**

Keywords—electroencephalogram, signal preprocessing, artifacts.

I. INTRODUCTION

With the emanation of non-invasive techniques, numerous research has been conducted on brain activity and related disorders. EEG tends to be a vital, noninvasive and cost effective technique accustomed monitor the state of the brain. The International Federation of Clinical Neurophysiology defines EEG as that (i) the science relating to the electrical activity of the brain, and (ii) the technique of recording electroencephalograms.

The EEG signal described as a nonlinear and non-stationary random weak signal[1]. On contrast with techniques as fMRI or PET,EEG has a high temporal resolution. The electroencephalogram records the cerebral electrical potentials by means of electrodes positioned over the scalp. The EEG has an amplitude of some 5 to 200 µV and is exposed to artifacts, from both bioelectric and physical sources[2]. The signal reflects the brain's functional state in addition to mental condition and this vital information is required in order to track patient's health [3].

II. EEG RECORDING AND PREPROCESSING

The brain signal has characteristic information in many regions at any given time. The EEG records voltage fluctuations by means of scalp electrodes, due to the flow of electrical charge for each excitation of the synapse in the neurons of the brain [4]. Here The noninvasiveness and inexpensive nature made EEG the most popular modality. The number of electrode varies from 1 to 256 for different EEG headsets. The EEG signals can be ordered based on their frequency bands each of which has specific biological significance.

TABLE I. EEG FREQUENCY BANDS

Band	Frequency	Amplitude (µV)	Location	Activity
Delta	0.5 – 4 Hz	100 – 200	Frontal and during deep sleep	Deep sleep
Theta	4 – 8 Hz	5 – 10	Hippocampus region	Drowsiness, Light sleep
Alpha	8 – 13 Hz	20 – 80	Occipital head region	Relaxed
Beta	13 – 30 Hz	1 – 5	Symmetrical distribution and most evident in the frontal and central head regions	Active thinking, alert
Gamma	>30 Hz	0.5 - 2	Widely over the cerebral cortex	Hyperactivity

The EEG electrodes appear as small metal disc made up of stainless steel or tin or silver alongwith silver chloride coating. These electrodes are placed in special positions on the scalp by means of internationally recognised system - International 10/20 system. EEG electrodes can be Wet or Dry electrodes. Traditionally wet electrodes made of Ag/AgCl were used. While recording the EEG, the electrodes not only pick up the clean brain signal rather it

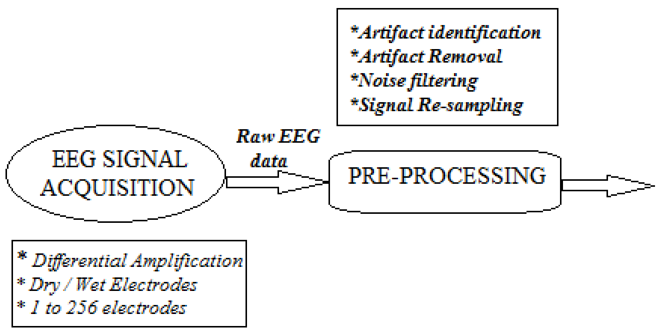

Fig 1. Pre-processing methodology

will be adultered with a variety of noise and artifacts. Following the recording step, preprocessing of the EEG signal is needed. Here, preprocessing refers to mainly removing noise , to urge closer to true neural signals and converting the information into a more useful format that may be useful for further analysis and research work. The principal pre-processing steps are the artifacts identification and removal, noise filtering, and re-sampling the signal to adjust to detector input specifications.

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III. EXISTING METHODOLOGIES

A. EEG Signal Filtering and Re-sampling

Artifacts – are signals recorded by EEG that is not of cerebral origin. The origin of artifacts may be physiological or extra-physiological. Physiological artifacts are generated within the patient (e.g., ocular movements [6], cardiac, eye blinks and muscular activity [7]) and extra-physiological artifacts are from outside the body or from external environment (e.g., EMI,50/60 Hz artifact, cable movements, electrode gel related). Ocular artifacts and myogenic artifacts pollute EEG signals; the former can be seen as relatively large pulses in the frontal region [8], whereas the latter can be seen as a wide frequency spectrum and that appears in the temporal and occipital regions [7].

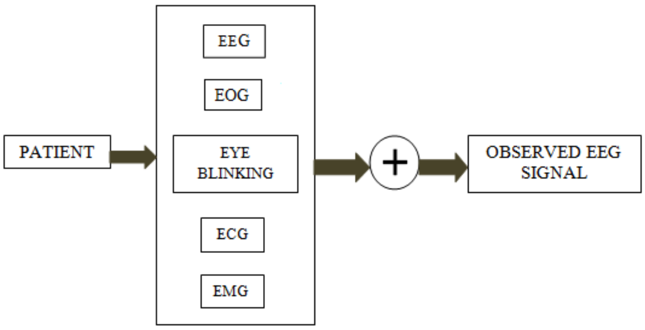

Fig 2. Bio-potential artifacts

Removal of artifacts needs careful consideration so as to retain the useful information of the EEG signal. Differential measurements prevent artifacts prompted by Electromagnetic Interference (EMI), mainly by power lines [5]. Good electrode placement avoids errors and eliminates artifacts [2].Wu Wen et al. [9]proposed a techniquewith which the EEG signals are used to detect the sleep quality. The electrophysiological signal - EEG has less amplitude and is highly prone to noise intervention. Hence, in the preprocessing stage, the signal is filtered to scale high-frequency noise, then it is split into 30s component so as to eliminate baseline drift and artifact interference which is illustrated by means of a flowchart.

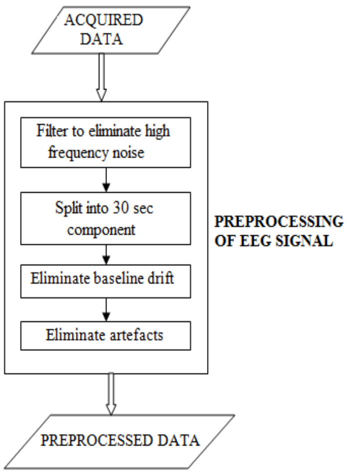

Fig 3. Flow diagram showing Signal preprocessing

Miao Shi et al. [10] proposed a method on EEG signals classification by pattern recognition method and the Support Vector Machine (SVM) And Optimization by means of Improved Squirrel Search Algorithm (ISSA). In this method, the preprocessing is done by (i)extract the time-domain features as feature vectors, (ii) feature vectors directed to SVM, and (iii) Classification and identification of the required data. To filter the acquired data, Miao Shi et al. uses an elliptical filter to extract the required information from the μ wave and β rhythm of the EEG signal which has the energy band within 8–30 Hz frequency. Here the elliptical filter has the pass band frequency that matches with the acquired waves' energy band during when the pass band ripples under 1 db and signal attenuation occur at a range of 5 Hz on each side of the pass band which is 40 db.

A multichannel Weighted Weiner filter been proposed here to reduce eye blink artifacts [11]. Both Hierarchical Fully Connected Topology (HFCT) and Ad-hoc Nearest-Neighbor Topology (ANNT) are competing existing approaches such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA), the proposed method achieves results for artifact attenuation that are 5% better. Unfortunately, actual medical gadgets have not yet used the suggested approach.

Hao Chao et al.[12] in his study proposed an EEG emotion recognition framework by combining multiband feature matrix and a capsule network (CapsNet). The Database for Emotion Analysis using Physiological Signals (DEAP) dataset was employed to validate the the proposed emotion recognition framework. From DEAP, the EEG dataset of signal frequency 512 Hz recorded with 32 electrodes were acquired. In the preprocessing stage, (i) the acquired EEG signals were down-sampled from 512 Hz to 128 Hz, (ii) the Electrooculogram (EOG) effects removed and, (iii) band-pass filtering implemented with cut-off frequencies set at 4.0 and 45.0 Hz.

Ho- Seung Cha et al.[16] proposed a method to anticipate every user's dynamic range of the EEG features and this helps in determining individuals who need additional calibration of the features. Initially, four EEG datasets are acquired - Resting state EEG (RS-EEG) dataset, the valence dataset, the relaxation dataset and the attention dataset. Here in the pre-processing stage all the datasets excluding attention dataset were down-sampled to 256 Hz, and the Multi-window Summation of Derivatives within a Window

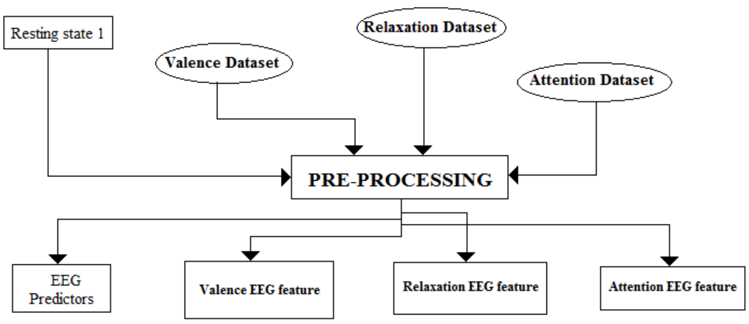

Fig 4. Flowchart showing the pre-processing method

(MSDW) algorithm is applied in which the EEG data (after down-sampling) were band pass-filtered at 0.5–30 Hz, segmented into a series of short segments, applying a sliding window of 1s length with an overlap of 50%. By means of visual examination the eye blink artifacts were discarded. For the attention dataset, 2-channel EOG signals below and right of the right eye were acquired and the ocular artifacts removed using least-mean square (LMS) based adaptive filtering. The EEG signals in the valence and relaxation

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datasets were not much affected by the eye saccadic artifacts and hence LMS filter not applied. For removing the ocular artifacts, the MSDW algorithm been applied as that doesn't require any additional EOG signal.

Narusci S Bastos et al. [14] proposed the EEG analysis based on two different band frequencies in EEG - full band and Beta band, through data mining. In this work, Narusci et al. focused in analyzing the Beta frequency band as this band is particularly associated with attention, visual precision, and coordination state of human. Here in the preprocessing, software is used and the steps are - (1) Conversion of raw EEG data (recorded without using filters) in graph data format (GDF) to comma-separated value (CSV), (2) Data labeling, (3) unwanted data cleaning and (4) Transformation of CSV data into Attribute- Relation File Format (ARFF), a machine learning format. Again, in another case study Narusci et al. [14] used a filter to pick out the Beta frequency band ie, between 13 Hz to 30 Hz.

Alexander Craik et al.[30]in his study specified that the study of various artifact removal did not address any specific artifact removal process. The familiar artifact-removal algorithms used were independent component analysis (ICA) and discrete wavelet transformation (DWT).

TABLE II. SIGNAL FILTERING METHODS PROPOSED IN THE LITERATURE

Filter	Type of Artifact removed	Advantages	Drawbacks
Low pass filter	Noise	Eliminates high frequency noise	Significant frequency components may be lost.
FIR Band pass filter	Noise	Allows only the selected band of frequency to pass through	
Elliptical filter	Particular band of frequencies	To extract information from μ wave and β rhythm of EEG Signal	Results in accuracy problems
Multichannel Weighted Weiner filter	Eye blink artifacts	5% better results compared to PCA and ICA	Not employed in real medical devices so far.
LMS based adaptive filter and MSDW algorithm	Eye saccadic artifacts and ocular artifacts	LMS – for removing eye saccadic artifacts and MSDW – for removing ocular artifacts	Convergence rate is low so that cannot be used in real time systems.

B. EEG Signal Decomposition

Gen Li et al.[13] presented an approach of maximum marginal on EEG signal pre-processing. In the preprocessing stage , a scalable and shiftable wavelet tends to break up the EEG data. At level 1, the EEG signal decomposed into the approximate component and detail component. The detail component at level 2 been calculated by employing wavelet transform on the approximate component at the level 1 component.

A deep-asymmetry technique is suggested by Min Kang et al.[15] that transforms the brain's asymmetry feature into a matrix-type image that is then supplied to a convolution neural network. The study makes use of the Hospital Universiti Sains Malaysia's (HUSM) open access EEG data set. The data were filtered between 0.5–70.0 Hz using a 50 Hz Notch filter to remove power line noise. 256 samples per second were taken for collecting the EEG data. Each channel was normalized using the min-max normalization approach during the data preprocessing stage. To eliminate EEG noise, the Independent Component Analysis (ICA) was applied. The 5 min data collection is split into 4 s epochs (1024 samples) for the data segmentation method in order to address the ML problem needs.

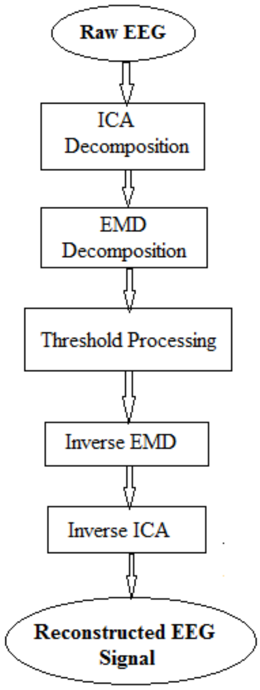

Fig 6. Process flow showing EEG signal preprocessing using ICA-EMD decomposition

Xiao zhong et al.[20] proposed an ICA-EMD based EEG signal processing algorithm to remove noisy artifacts from EEG signals. (a)By means of ICA, the multichannel EEG recording is decomposed into statistically independent components, and (b) by applying EMD filtering the elimination of physiological artifacts in single-component EEG were achieved. The experiment shows that the ICA-EMD algorithm effectively eliminates the artifacts thereby retaining the useful neural information.

C. EEG Signal Processing with Graphic User Interface (GUI)

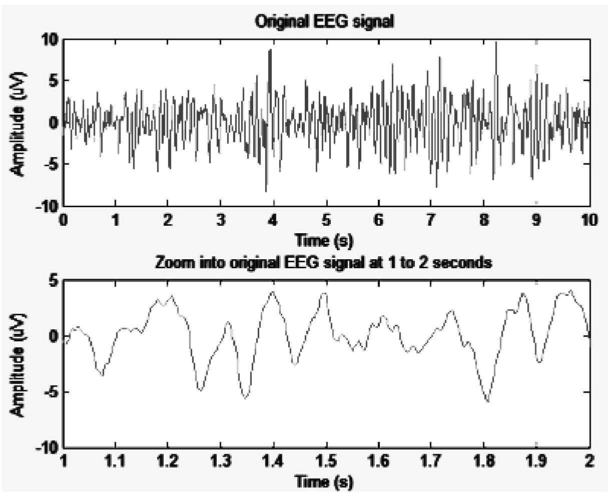

Fig 7. Original and processed EEG signal using MATLAB

Alejandra L. Callara et al.[17] presented a framework to study the brain related activity in the case of Cheyne-Stokes Respiration patients with the help of EEG signal.

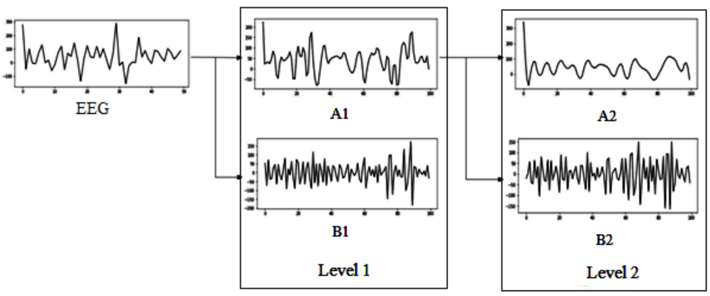

Fig 5. Decomposition of EEG at two levels

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Initially, the acquired data including EEG were sampled at a frequency of 512 Hz and filtered with a two pole anti-aliasing low- pass filter with -3dB at 105 Hz on all channels. With the help of an interactive GUI toolbox, EEGLAB, the EEG data were high-pass filtered above 1 Hz with a wavelet-based, thereby enhancing stationarity. To remove line noise, an adaptive method is utilized which omits the line-noise-related sinusoidal artifacts. After filtering, the identification of bad channels done with the help of a Kurtosis-based approach (Z-score threshold: ±10) Visual inspection is performed to remove the corrupted data segments which in turn allows proper ICA decomposition.

Haoran Liu et al.,[18] in this paper described the steps involved in the emotion recognition algorithm using EEG while reviewing the existing EEG- based emotion recognition methods along with assessment of their classification effect. The preprocessing of EEG signal is done using EEGLAB which performs the tasks such as channel identification, filtering, baseline correction and independent principal component analysis. The dataset acquired from open datasets of affective computing. After importing EEG data to EEGLAB, filtering the noise in the signal performed by means of suppressing the signal. To remove the electromagnetic interference, the Butterworth band-pass filters are used.EOG artifacts been removed with the help of either regression method or adaptive filtering method.

Ala Hag et al.[19] proposed a novel methodology that

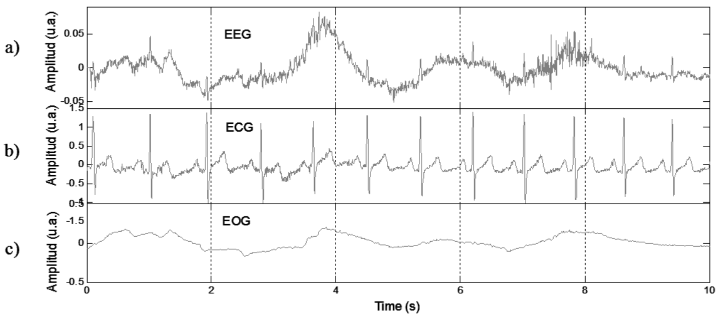

Fig 8. Separation of ECG and EOG signal from the corrupted EEG signal

identifies the mental stress by scrutinizing the statistical difference between stress and rest conditions. The EEG signal data is acquired and is sampled at 256 Hz frequency. Here in the Preprocessing stage, Python and an external MNE package is used. (i) The unprocessed EEG signals filtered using a band-pass finite impulse response (FIR) filter between 1 Hz and 35 Hz bandwidth. (ii) Power-line noise of 50/60 Hz excluded. Furthermore, (iii) Fast-ICA performed to eliminate the noise ocular artifacts (EOG) under 4 Hz, muscle artifacts (EMG) beyond 30 Hz, and cardiac artifacts (ECG). In frequencies less than 16 Hz, Fast-ICA exhibits an unique ability of de-noising ocular artifacts (OAs).

D. *Signal Cutting - EEG*

Giuseppe Varone et al.[21] in his paper proposed a data based machine learning (ML) pipeline consisting of a semi-automatic signal processing technique along with supervised ML classifier to aid in the diagnosis of Psychogenic Non-Epiletic Seizures(PNES) by means of EEG data. The acquired EEG signal is down sampled at 256 Hz and segmented into 20 minute records. While pre-processing the signal, to avoid imbalances the 20 min long records changed to 15 min records. Then the EEG data were manually reviewed to label and reject the artifactual time series such as (i) Eye blinking/ EOG, (ii) Muscular movement /EMG, (iii) Heart rate / ECG, and (iv) electrode artifact. Then the manually reviewed signal were band pass filtered between 1 and 70 Hz with the 3rd order Butterworth band pass filter of 50 Hz to obtain the important EEG rhythms. At the end of the 20 minute recording, clean EEG time series were obtained and segmented into non-overlapping EEG epochs. Each EEG epoch are of size, L = 5s and therefore 1280 samples obtained. With the help of handwritten Matlab 2018a algorithms, each one of the EEG epochs are preprocessed individually and later stored as .mat files.

E. *EEG Processing in BCI system*

In their work, Mamunur Rashid et al.[22] gave a clear overview of EEG-based BCI systems, as well as the pre-processing strategies involved, suggested feature extraction methods, existing classification algorithms, evaluation metrics utilized. This allows the reader to choose the best approach for their specific BCI system. Mamunur Rashid et al. explains that pre-processing is a laborious process, since it eliminates any undesirable elements that may lodged in the EEG signal. A more effective preprocessing technique enhances signal quality, feature separability and thereby classification performance. Low, high, and band pass filters are the most common and efficient way to reduce artifacts when there is no signal overlap in the measured EEG [13]. Several artifact removal methods, including adaptive filtering, Wiener filtering, Bayes filtering [23], Common Average Referencing (CAR) [24], and blind source separation (BSS) [25] are used when there is spectral overlap. SuBAR (Surrogate-based Artifact Removal) , a data-driven technique, successfully eliminates muscle and ocular artifacts from EEG [26]. The combination of EEMD-and IVA has been shown to perform better than other existing approaches in situations when there are a limited number of channels [27].

The joint BSS approach and quadrature regression IVA (q-IVA) removes artifacts effectively in both the time and frequency domains [28]. The combination of BSS and Regression (REG), which is an online EEG artifact attenuation, can be used for BCI applications [29].

IV. Results and Discussion

It has to be noted that Pre-processing of EEG signal refers to transforming the raw EEG data into a suitable format that can be used for further analysis. And so, various researchers used different pipelines based on their application. In general, EEG tends to record the electrical activity of the brain and is prone to artifacts which are either physiological or non-physiological in nature. Physiological artifacts include EOG, EMG and ECG whereas the main non- physiological artifacts are EMI, 50/60 Hz artifact, cable movements, electrode paste-related and so on.

From the above study, it was stated that the ocular artifacts can be removed effectively by means of band-pass filtering with cut-off frequencies of 4.0 and 45.0 Hz.[12], LMS-based adaptive filtering with 2-channel EOG measurements [16], Fast-ICA for ocular artifacts in low

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frequencies less than 16 Hz.[19], SuBAR to remove muscular and ocular artifacts [26],Regression method[18] and Adaptive filtering with stability and fast convergence [18].

In order to remove muscular and cardiac artifacts, Fast ICA with frequency beyond 30 Hz been proposed[19] and the particular time series will be rejected[21] or band pass filtered between 1 and 70 Hz [21]. And the non-physiological artifacts such as EMI by power lines can be removed by implementing differential measurement techniques to record EEG [4], use of Butterworth band-pass filters [18], filtering in the range of 0.5 to 70.0 Hz with 50 Hz notch filter [15]. For removing line noise, an adaptive method that subtracts line-noise-related sinusoidal artifacts been deployed[17].The noise caused by 50/60 Hz of line power was removed [19].

For attenuating eye blink artifacts, a multichannel Weighted Weiner filter been presented [11]. Miao Shi et al. uses an elliptical filter to acquire the information from the μ wave and β rhythm of the EEG signal (8-30 Hz)[9].Xiao zhong et al.[20] proposed an ICA-EMD based EEG signal processing algorithm to remove noisy artifacts from EEG signals. In case of eye saccadic artifact attenuation, the MSDW algorithm is proposed [16].

In few other studies, the researchers utilized different methods in addition to artifact removal step in the EEG preprocessing phase. Gen Li et al. utilizes wavelet transform to break down the EEG signal for calculating the frequency components [13].

Narusci et al. [14] in the preprocessing phase converts EEG data (recorded without using filters) in graph data format (GDF) into ARFF, a machine learning format which is suitable for further data mining software. Min Kang et al. [15] normalized the EEG data using the min-max normalization method. The ICA was used to remove EEG noise.

Ho- Seung Cha et al.[16] by using MSDW algorithm detected time periods with eye blink artifacts and are data segmented. Data segments with eye blink artifacts were excluded. The EEG data were high-pass filtered above 1 Hz with a wavelet-based filter and this improves stationarity. After filtering, the presence of bad channels identified by means of a kurtosis-based approach (Z-score threshold: ±10), The corrupted data segments were removed by visually inspecting the data. [17].

The preprocessing of EEG signal includes channel location, filtering, baseline correction and principal component analysis using EEGLAB [18].

The experts reviews and reject the artifactual time series such as (i) Eye blinking / EOG, (ii) Muscular movement / EMG, (iii) Heart rate / ECG, and (iv) Electrode artifact [21]. ICA is an effective method for removing artifacts though it disregards the temporal or spatial relations within sources and results in the loss of relevant information. And again due to its minimum time consumption, CCA can be utilized for real-time applications [30]. As per the principle of BSS algorithms, more number of channels are required in order to be more accurate. For which the wavelet transform and EMD based methods require a single channel but can be decomposed into multiple components. After which the number of channels can be reduced which eventually increases the computational complexity and this becomes a major limitation for BCI application [30].

From our review, it is clear that ICA-based algorithms deal with all kinds of artifact occurred in EEG recordings. ICA and CCA rather than being alone their combination with other methods seems to be an interesting choice for removal of muscle artifacts. For applications using few channels, EMD, IVA, and its fusion methods with BSS or WT becomes a proper choice. The necessity of reference signal limits adaptive filter or regression methods, to be utilized for the removal of artifacts. Artifacts when overlapped with spectral properties, the wavelet transform is not suitable. EMD suffers from the drawback of mode-mixing. Accordingly, it is strenuous to find a single method that is both efficient and accurate enough to assure all the conditions.

In addition, the automatic methods are not advised for artifact removal, as there are multiple types of artifacts that exist in the recordings. The manual rejection of segment directly neglects the epochs contaminated by artifacts but there is a possibility of losing vital information from the EEG signal [9]Good electrode placement avoid errors and eliminates artifacts [2].

TABLE III. SUMMARY OF THE EEG PREPROCESSING METHODS

Methods discussed	**Purpose**
Band pass filtering with cut-off frequencies at 4.0 and 45.0 Hz [12]	Ocular artifacts can be removed
LMS based adaptive filtering [16]	EOG removed
Fast ICA with freq less than 16 Hz[19]	Ocular artifacts in low frequencies less than 16 Hz.
Surrogate based artifact Removal (SuBAR) / Regression method [26]/ Adaptive filtering [18]	To remove muscular and ocular artifacts
Fast ICA with frequency beyond 30 Hz [19] / Band pass filtering between 1 and 70 Hz [21]	To remove muscular and cardiac artifacts
Multichannel Weighted Weiner filter [11]	To attenuate eye blink artifacts
Elliptical filter [9]	To acquire information from μ wave and β rhythm of EEG
ICA – EMD [20]	To remove noisy artifacts from EEG
Multi-window Summation of Derivatives within a Window [16]	To remove eye saccadic artifacts
Wavelet transform [13]	EEG signal decomposed to calculate the frequency components
Data mining software [14]	EEG signal converted to machine learning format – ARFF.
Min-max normalization method [15]	Each EEG channel been normalized followed by ICA to remove noise.
Wavelet filter (High pass filtered above 1 Hz) [16]	To improve stationarity of the Signal.
Kurtosis – based approach [17]	Determines the presence of bad channels.
GUI – Matlab [18]	Performs tasks such as channel location, filtering, baseline correction and ICA.
Wavelet transform and EMD based methods [30]	For Blind Source Separation algorithms involving more number of channels.
Elimination of time series [21]	Experts label and rejects the artifactual time series by review.

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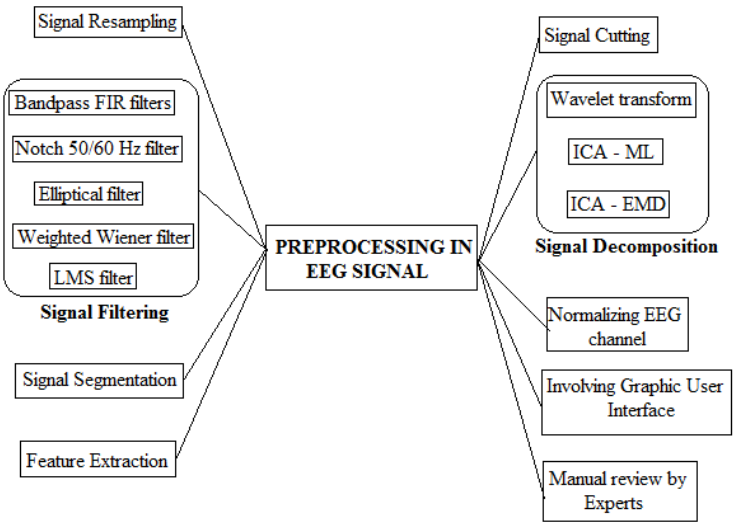

Fig 9. Pre-processing techniques suggested for acquiring useful information from the EEG Signal

V. Conclusion

From the above discussion we conclude that it is complicated to find a unique method that fits to satisfy all the conditions perfectly. Among the many artifact removal methods/ algorithms available in the literature, some are used to remove only particular artifacts such as EOG, ECG, and EMG. In some cases, the methodology requires reference channel to enhance the accuracy. Again when it comes to online applications the methods are highly complex and that makes it as not suitable. Hence, from the above discussion, we conclude that there is no exceptional choice to remove all types of artifacts from an EEG signal. Such published techniques were proposed by progressing existing algorithms or by combining various methods or making removal process a real-time process by means of machine learning. As EEG preprocessing is still an ongoing area of research study, there is no comprehensively approved EEG preprocessing pipeline, and that researchers have some privilege in choosing how to transform the raw data. Good preprocessing increases the signal quality, and thereby results in enhanced feature separability and better classification performance [22]. Apart from this, as a precaution the artifact avoidance can be tried to avoid unnecessary motion.

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