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Fully Automated Artifact Removal for BCI

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Abstract: A common problem faced by any of the devices concerning BCI applications (Brain Computer Interface) is that of the Artifacts. The undesired electrical signal interfering with the neurological activities of the brain as a consequence, misinterpreting the actual signal. The artifact may be generated internally or externally. The proposed method aims to reduce some of the predominant artifacts generated through the Electroencephalogram (EEG) such as eye blinks or artifacts generated from other devices such as Electroocculogram (EOG) or Electromyogram (EMG) . It is based on a novel combination of wavelet decomposition, Independent component analysis and thresholding. The factors for identifying the artifacts are estimated which differentiates the clean from affected EEG signal. We also intend to calculate the computational time of our proposed method for an EEG signal of 1s time frame.

Keywords: Brain Computer Interface, Artifacts, Electroencephalogram (EEG), wavelet decomposition, Independent component analysis.

I. INTRODUCTION

An area concerning biomedical engineering in which engineering principles and design concepts are applied with respect to medicine and biology for healthcare purposes has been of thriving research interest lately.The **brain computer interface** (BCI) is a direct communication pathway between brain and an external device. The purpose of using BCI is for assisting or repairing human cognitive or sensory motor function [1].The most preferred non-invasive device is the **Electroencephalogram (EEG)**. The EEG is a device which measures the electrical signals produced from brain due to brain's electrophysiological activity. Despite poor special sensitivity, The EEG is most preferable due to the following advantages,

- Hardware cost is significantly lower compared to other techniques such as functional magnetic resonance imaging. Magneto encephalography (MEG), positron related tomography to name a few.
- It has the advantage of portability compared to above mentioned techniques.
- It has a very high temporal resolution which is in the order of millisecond rather than seconds.
- EEG does not involve exposure to high intensity magnetic fields (>1 tesla) compared to Magnetic Resonance Imaging (MRI) or MRS.
- In EEG, there is better understanding of measurement of signals as compared to MRI.
- Electrical signals arising due to excitation in the sensory neurons caused by miscellaneous/unwanted activities gives rise to a condition called artefacts.

Common methods to remove these artifacts include wavelet based denoising and blind source separation method (BSS).Blind source separation, could be considered as identifying and separatinga set of individual source signals from a set of mixed signals, without the help of information (or with very little information) about source signals or the mixing process.Similar method includes the Wavelet transform which performs a correlation analysis, therefore the output is expected to be maximal when the input signal resembles the mother wavelet considerably. Similar methods of artifact removal methods include Independent Component Analysis (ICA) and Support Vector Machines (SVM). ICA is a computational method used for isolating a signal of multivariate nature into added substance subcomponents. This is calculated by inferring that the subcomponents are non-Gaussian signals and that they are statistically autonomous from one another. However the ICA techniques are usually optimized for the Electroocculogram (EOG) and the Electromyogram (EMG), and differentiating the EEG from these signals are quite limited.Hence, considering the characteristics of the wavelet based decomposition and the ICA methods, we intend to combine these two techniques to improve the overall performance in the process with respect to artifact removal. The following sections in this paper are as follows. The first section gives a brief introduction concerning the significance of the area of interest and the general problems associated with it. The second section gives a brief introduction regarding the prerequisites necessary for better understanding of the subject. A review of literature and related works is given in section 3. The proposed system and implementation concerning the architecture and work flow of the project is given in section 4 and 5 respectively. The obtained results is given in section 6 and finally the conclusion of the overall work along with references is given.

BACKGROUND

A. Brain Computer Interface (BCI) and EEG

The BCI acts as a link between the brain and the device to be controlled (external device). The primary application of BCI is to assist/repair the cognitive and sensory motor function. Types of BCI include invasive BCI which can be defined as devices implanted directly into the grey matter of the brain, and non-invasive BCI that is devices which the participant has to wear manually. Devices pertaining to Non-invasive BCI are much preferred devices because it is non-surgical and it caters to a wide range of applications. A preferred device for the purpose of procuring signals from the brain for the BCI application is the electroencephalogram (EEG). A typical EEG is shown in fig.1.

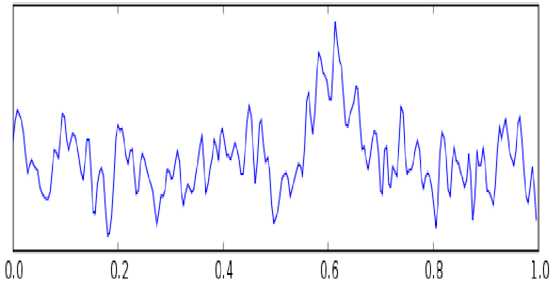

Fig.1: An ideal EEG signal

B. Artifacts

Electrical signals detected along the scalp by an EEG, but that originating from non-cerebral origin are called Artifacts. In other words it could be described as undesirable electrical activity observed in the signal but not related to brain activity which could lead to contamination of EEG amplitude as a consequence misinterpreting the actual signal. Basic types of artifacts include

- Eye induced artifacts (eye blinks, eye movements, etc.)
- Artifacts induced by Electrocardiography (ECG)
- Artifacts induced by Electromyography (EMG)

Some of the methods used for artifact removal is given in the following subsections.

C. Wavelet decomposition

The wavelet based analysis is primarily used to functionally localize signals into time and frequency space. The wavelet based techniques are very effective in processing of non-stationary signals such as EEG signals. The wavelet signals basically decomposes the signals into wavelets by using wavelet functions called as the ‘mother ‘ and ‘Father’ wavelet functions.

If a signal possess energy which is concentrated in a small number of WL dimensions, its respective coefficients will be relatively large with respect to any other signal or noise that its energy spread over a large number of coefficients, This means that shrinking the WL transform will remove the low amplitude noise or undesired signal in the WL domain, and an inverse wavelet transform will then retrieve the desired signal with little loss of details, hence it is preferable to consider this technique in the process of artifact removal but it lacks accuracy and takes high computational time in real time/online systems.

D. Independent component analysis

Independent Component Analysis (ICA) is a computational technique for isolating a multivariate signal into added substance subcomponents. ICA finds the Independent segments (additionally called factors, latent variables or sources) by optimizing the statistical independence of the assessed components. We might pick one of numerous approaches to characterize a proxy for independency, and this decision oversees the type of the ICA calculation. The two broadest meanings of independence for ICA are

- Minimization of common data
- Amplification of non-Gaussianity

The Minimization-of-Mutual Information (MMI) group of ICA calculations utilizes measures like Kullback-Leibler, Divergence and maximum entropy. The non-Gaussianity group of ICA calculations, propelled by the central limit theorem, utilizes kurtosis and negentropy.

Regular calculations for ICA use centring (subtract the mean to make a zero mean signal), whitening (ordinarily with the eigenvalue disintegration), and dimensionality reduction as pre-processing ventures keeping in mind the end goal to improve and lessen the multifaceted nature of the issue for the actual iterative calculation. Pre-whitening, dimensional reduction and mixing matrix could be accomplished with the help of Second Order Blind Identification Algorithm (SOBI). Pre-Whitening guarantees that all measurements are dealt apriori before the calculation is executed. However, ICA could not recognize the actual number of source signals.

E. Properties and measures concerning artifact removal

The identification and removal of artifacts is based on certain measures of the properties pertaining to EEG signals. Some of them are:

1. Kurtosis :In general Kurtosis could be calculated as a pdf for a random variable having real value. This measures the peakedness of the data corresponding to its variance. The projections of each IC’s obtained from the demixing matrix is considered where the mean is calculated for these projections and a threshold is applied with respect to this kurtosis value as shown in (1).

$$k > \left(\mu(k) + \left(0.5 \text{ X } \sigma(k)\right)\right) \quad (1)$$

Where, k ← kurtosis of scalp projection of a single IC, $\mu(k)$ →mean of the kurtosis values over scalp projections of all the values, σ (k) → standard deviation

1. GammaPSD :The gammaPSD measure is usually used for the purpose of detection of EMG induced artifact inside the EEG signal. The power spectra of EEG signal follows a 1/f distribution in the gamma frequency band of frequency range above 30 Hz.

2. Auto mutual information: Auto mutual information is a measure for detecting the temporal deficiency present in the EEG signal which could indicate the

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presence of an artifact. The measure of AMI can be given in (2) and (3)

$$AMI_{\tau} = MI\ (x(t), x(t+\tau)) \quad (2)$$

Where, MI $\rightarrow$ mutual information, $\tau \rightarrow$ time lags

$$MI(X) = \sum_{i}^{N} H(X_i) - H(X_1, X_2, \dots X_N) \quad (3)$$

Where, $H(X_j) = -\sum_{i=1}^{N} p(x_i) \log p(x_i)$ and

$$H(X_i, \dots X_N) = \sum_{x_1} \dots \sum_{x_N} p(x_1, x_2 \dots . x_n) \quad (4)$$

$$\log(p(x_1, x_2, \dots, x_n)) \quad (5)$$

Equation(4) and (5) represents the entropy and joint entropy respectively of the random variable X estimated at $x_i, i = 1 \dots T_m$. Where $T_m \rightarrow$ denotes number of samples in each realisations in X.

II. LITERATURE SURVEY AND RELATED WORKS

An extensive review of literature has been done in the field of BCI applications concerning the artifact removal in EEG signals. Some of these methods are mentioned below.

A. Linear filtering based artifact removal

Linear filtering approach is considered as the most simple and practical approach for the purpose of artifact removal which could span over a particular range of frequencies on a spectrum. P. Dhankar and S. Khaleri [2] signify a method for reducing the eye blink artifact (EBA) in EEG signal using FIR filter. The method also improves the Signal to Noise ratio.

A.G Reddy and S. Narava [3] also shows the types of artifacts effects EEG signals and the methods to reduce the artifacts in EEG signals using Linear filtering but, indicates that the method fails to perform when it comes to artifacts such as power line noise and baseline noise. In order to overcome this problem adaptive linear filtering is subsequently used after performing linear filtering. The main limitation of using linear filtering is that it does not clearly differentiate the artifacts in EEG signals with respect to frequencies concerning the neurological activities of the brain, This limitation is a consequence of overlapping of frequencies of neurological signals and that of the artifact generated signals. A limitation noticed in using LMS filtering is that it fails to distinguish between EEG and EOG signals, as a consequence it removes part of the EEG along with EOG signal removal. J. Dhiman et al. [4] performs a comparative evaluation between adaptive filter algorithms such as LMS, NLMS and RLS (Recursive Least Square) to name a few. A trade-off between complexity and convergence is observed. Examining these algorithms based on their complexity and Signal-To-Noise Ratio (SNR), The RLS algorithm seems to possess higher SNR values compared to earlier algorithms based on stochastic gradient approach. The performance of RLS algorithm is at its best in time varying environments, but as a consequence increases the system complexity along with some stability problems. The performance criteria in this work for evaluation of algorithms include minimum mean square error (MMSE), algorithm execution time and required filter order.

B. Blind Source Separation

This method in general represents a nondeterministic condition; However, some useful conditions could be derived under a surprising variety of conditions. Some of the methods defined under BSS are,

1. Principal Component Analysis

L. I. Smith [5] defined the PCA as a statistical procedure that uses an orthogonal transformation for theconversion of a set of observations which are possibly correlated variables into a set of values of linearly uncorrelated variables called the Principle Components based on the maximum variance of the values.

Berg et al. [6] reports that the PCA method outperforms that of the regression based methods. The work in [6] primarily highlights the significance of PCA method in calculating covariance of the chemical component in the dataset. The experiment was to trace the elements and main components in precipitation falling on Norway.

G. L Wallstrom et al. [7] addressed the problem of regression based methods with respect to artifact removal in EEG by combining regression based approach with automated PCA. The work in [7] performed a comparative study on regression methods using adaptive Bayesian adaptive regression splines to filter EOG before computing correction factors. They also observed that an automated PCA method reduced the Ocular artifacts and resulted in minimal spectral distortion. Therefore they suggested the need for combining the regression based methods and PCA methods. However, The PCA methods could not distinguish between artifacts having similar amplitudes such as eye blinking, ECG and EMG.

M. E. Wall et al. [8] addressed the limitation of recognition of artifacts with similar amplitudes in a way of gene expression analysis, where he tries to combine the PCA method with Single Value Decomposition (SVD). He also tries to obtain a relation between the PCA method and SVD method when PCA is calculated using covariance matrix enabling the descriptions to be applied equally well to either of the methods.

However, the limitation in PCA was that the source signal has to be orthogonal and this method was effective in only decorrelating the signals, As a consequence its performance decreased when it came to higher order statistical dependencies. In order to overcome this drawback the Independent Component Analysis (ICA) method was incorporated which is an extension of PCA.

2. Independent Component Analysis

The ICA method performs a better decorrelation of signals having higher order statistical dependencies.
R. Vigario et al. [9] performed a study for identification and removal of artifacts in magneto encephalographic

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recordings. They analysed that the ICA method could clearly identify and isolate the produced artifacts.

M. Ungureanu et al. [10] performs an analysis on the ICA methods in applications pertaining to biomedical signal processing and also detected and removed redundant information in signals corresponding to respiratory problems. In the instance of EEG analysis, each source pertaining to artifacts projected a unique topography onto to the scalp-scalp maps. These maps were mixed according to the principle of Linear Superposition. The work in [10] inferred that the important information could be obtained after applying ICA method considering only to the relevant signals.

Bell and Sejnowski [11] originally proposed an ICA method called the Information maximization algorithm (INFOMAX) which separated the unknown source signals from a mixture of signals by performing gradient ascent to the signals. However this method proved to be efficient considering only a small number of signals. To perform on larger number of signals improvement on gradient ascent method was proposed.

A. J Bell and T. J Sejnowski [11] proposed an approach for blind Separation and Blind deconvolution method by extending the Infomax algorithm. The result obtained was a generalization which satisfied the general stability criterion formixed sub-gaussian and super-gaussian sources. A comparative analysis between the Infomax and the extended Infomax algorithms resulted the latter separating a wider range of source signals while still maintaining the simplicity of the former algorithm. With respect to EEG signals it showed effectiveness in separating the artifacts such as eye blinks, line noise from weaker electrical signals.

J. F. Cardoso [12] considers a higher order measure of independence for ICA analysis and discusses the class of Jacobian algorithms for their optimization. A comparative analysis was computed based on gradient based techniques with respect to algorithmic view-point and on a set of biomedical data.It has been demonstrated that signal separation techniques such as JADE and Extended ICA algorithm more effective than EOG subtraction and PCA for removing ocular artifact from EEG.

AapoHyvärinen [13] of Helsinki University of Technology had invented an ICA method which seeks an orthogonal rotation of prewhitened data, by a fixed point iteration scheme that maximises the measure of non-gaussianity of the rotated components. The method came to be known as fast ICA method.

J. W Williams and Yan Li [14] performed a comparative analysis of known ICA algorithms which shows the performance of JADE (Joint Approximation and Diagonalisation of Eigen matrices) algorithm (work in [12]) and the fast ICA algorithm with respect to Power Signal to Noise ratio (PSNR), The fast ICA had an advantage over JADE algorithm with respect to PSNR.

C. J Barrera et al. [15] pointed out that the ICA algorithms were not automated (Automatic selection of thresholding), as a result they required visual inspection of independent components for decision of their removal.

Nicolau et al. [16] proposed a method to address this issue of automated artifact removal by applying a specific application called Temporal Decorrelation Source Separation (TDSEP). An advantage of this method is that since the separation is based on correlation of sources, TDSEP can separate signals which have a Gaussian Amplitude Distribution.

One of the drawbacks noticed in ICA methods was that the performance of the ICA methods were dependent on the size of the dataset, Also it was observed that the performance was low for small datasets.

C. Wavelet Based denoising

J. W Williams and Yan Li [14] indicate the concept of detail and the approximation coefficients in wavelet transform. The omission of the small detail might be performed without affecting the main signals by Thresholding. There are two types of thresholding soft thresholding and hard thresholding. The work in [14] also states that the soft thresholding has better mathematical characteristics than hard thresholding and it also provides smoother results as compared to the latter. they show the transformation method pertaining to Discrete Wavelet Transform (DWT).

C.J Barrera et al. [15] showed another type of Wavelet transform is the Wavelet Packet Transform (WPT) which divides the approximation and detail coefficients at each level forming a binary tree. By considering an appropriate filter any part of the binary tree can be selected such that an orthonormal decomposition of the signal is produced. They also showed that the WPT method had a high robustness and low distortion for compression ratio in the range 5-8 after applying compression-decomposition process for EEG signals. The WPT method also had a relatively low computational cost which makes it more appropriate towards practical applications.

However, a drawback observed in wavelet based transformations is if the signal and artifact have similar or higher values with respect to their amplitudes, then the wavelet has difficulty in distinguishing between them.

It is observed that the wavelet based denoising methods and the BSS methods complement each other with respect to their drawbacks. Considering the three general methods for removal of artifacts in EEG signal which includes linear filtering, blind source separation and the wavelet based decomposition methods. The work in [15] tries to perform a novel combination between the ICA methods and the wavelet decomposition methods. The performance evaluation shows an increase in the PSNR and MSE (Mean Square Estimation). They concluded that a combination of ICA and Wavelet based decomposition

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methods showed better performance with respect to above mentioned parameters than compared to individual methods pertaining to ICA and Wavelet based decomposition methods.

III. PROPOSED SYSTEM

The work in our project is considered mainly in the pre-processing stage in the overall BCI applications. The purpose of pre-processing stage in a BCI application is to reduce the artifacts in the EEG signal generated from various sources such as eye blinks, EOG and EMG interferences etc. and generate a cleaned EEG signal for further operations. Basically the artifact removal process involves four steps (as shown in fig.1), they are,

- obtaining the EEG raw signal
- decomposition of signals into individual components.
- Identification of signal containing artifacts based on some measurements with respect to its signal properties.
- Generating cleaned EEG signal by separating the artifacts from the EEG signal by thresholding.

1. Pre-processing of EEG data: Its main functionality is to perform sampling of the data, recognize channel properties, perform thresholding for spiking activities and identify the channels in frontal locations.
2. Wavelet based decomposition: performing decomposition based on discrete wavelet transform and produce detail coefficients and approximation coefficients for the pre-processed EEG signal.
3. Independent Component Analysis: This section considers the approximation coefficients and separates the channel components which were combined linearly into individual components by calculating a mixing matrix using a second order blind identification algorithm.
4. Identification of Artifact contaminated IC's : This section identifies the IC's contaminated by artifacts by considering certain measuring parameters with respect to channel properties and consequently separates the IC's by applying soft thresholding and thus removing the artifacts.

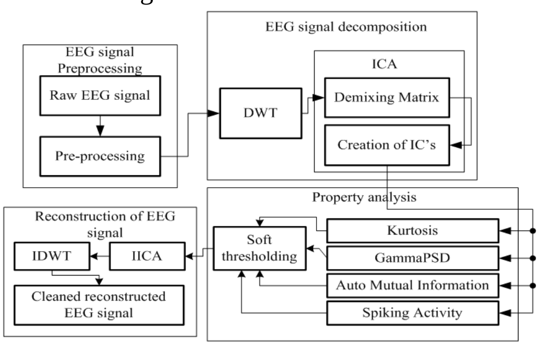

Fig 1: proposed system

5. Reconstruction of EEG signal : This section involves the computation of Inverse ICA for calculating the mixing matrix and inverse DWT for the final reconstruction of cleaned EEG signal.

IV. IMPLEMENTATION

The procedure for the implementation for the artifact removal (as shown in fig. 2) is given as follows.

1. First we consider a database having raw EEG signal along with its channel properties and channel locations. Consequently we sample the signal at 500 Hz sampling rate. We then apply thresholding for the purpose of detecting abnormal spikes in the EEG signal. We then identify the channel with frontal locations considering the artifacts taken in our work.
2. We apply Discrete Wavelet Transform considering the 'symlet' wavelet transform for the obtained frontal channels in the EEG signal. Consequently we consider the Approximation Coefficient (AC) obtained by DWT for IC analysis.
3. In ICA we first apply pre-whitening for the obtained AC's and then perform joint diagonalisation in order to calculate the mixing matrix to obtain the linear relationship between the AC's. By using the mixing matrix we then obtain the Independent Components (IC's).
4. In order to identify the artifacts in the IC's. An analysis on the measure of properties such as kurtosis, gammaPSD, AMI and spkiking activities concerning the artifacts in the EEG signals are considered.
5. Soft thresholding is applied to the above measures exceeding which the IC's will be identified as IC's contaminated of artifacts.
6. The remaining IC's (i.e. IC's not exceeding the thresholding value) are considered where Inverse ICA and Inverse DWT is applied to obtain the cleaned EEG signal with reduced artifacts.

V. SIMULATION RESULTS AND PARAMETRIC EVALUATIONS

The obtained simulation results are shown in fig.3 and fig.4 along with the corresponding graphs with respect to gamma PSD which is shown in fig 5 and fig.6.

The Raw EEG signal is shown in fig.3 where the artifacts are detected in the first four channels. By applying the proposed method, the artifacts were successfully removed producing a cleaned EEG signal which is shown in fig.4.

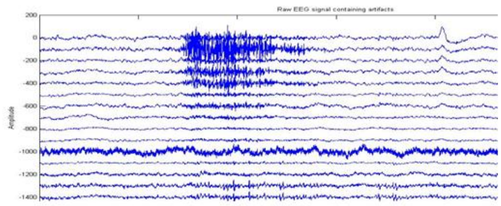

Fig.3 : raw EEG signal

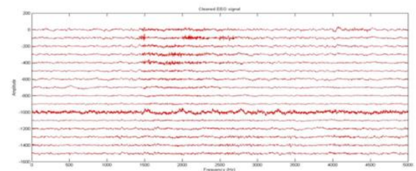

Fig 4: cleaned EEG signal

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The comparative analysis of both raw and cleaned EEG signal based on gamma PSD is shown in fig.5. It can be inferred from fig.5 that the obtained cleaned EEG signal has a lower PSD than the original raw EEG signal.

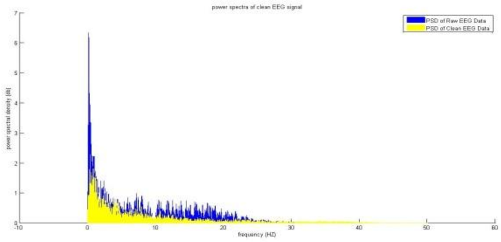

Fig 5: comparative analysis of raw and cleaned EEG signal with respect to its PSD.

VI. CONCLUSION

The proposed method for the purpose of artifact removal with respect to artifacts such as eye blinking, EMG and EOG is achieved successfully. The process of using a combination of wavelet based de-noising and ICA method proved to be an efficient way in reducing artifacts and also increase the system efficiency in terms of computational cost, reliability and performance. Also different methods of calculating the mixing matrices could be used for the purpose of derivingthe linearity relationship between the sources.

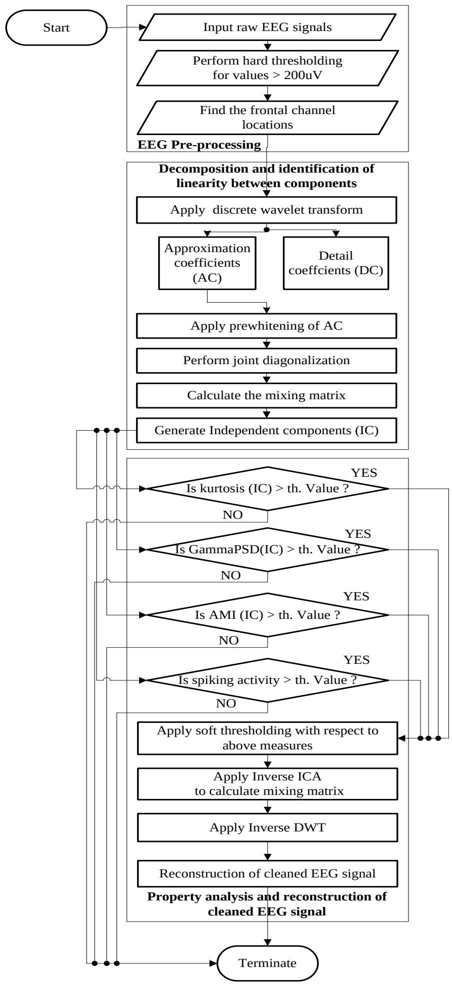

Fig 2: The flow diagram for artifact removal process

This method was able to operate on EEG database having 16 channels and did not require any additional signals. This method is very much useful in the pre-processing stage in the BCI applications. In the future scope more number of artifacts could be detected by conjoining more techniques with respect to their artifact removal capabilities. One example would be using linear filtering due to its simplicity and robustness of the system.

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