A Survey on Methods on Artifact removal from EEG

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ABSTRACT
Important methods concerning artifact removal from EEG signals has been briefly described pertaining to its significance and its drawbacks. Some methods described herein range from conventional methods such as linear filtering, Linear combination and regression (LCR) to more contemporary methods such as blind source separation (BSS) with applications such as Principal component analysis (PCA) and Independent component Analysis (ICA) including the more recent wavelet based transformation methods (such as Discrete Wavelet Transform and Wave Packet decomposition). It is observed that these methods complement each other in perspective of their drawbacks, therefore a novel combination in some of these methods particularly the ICA and Wavelet based Transform results in a much better balance between statistical considerations, practicality and computational efficiency.

General Terms
Filtering based methods, components based analysis, wavelet based transformation.

Keywords
Linear filtering, LCR, BSS, ICA, PCA, Wavelet based Transformation**.**

1. INTRODUCTION
The Electroencephalogram (EEG) was originally discovered by a German scientist named Hans Berger in 1924 in order to study the neurological activities of the brain (also known as brain waves).Electrical signals are produced from the brain as a consequence of some particular activities due to excitation of neurons. The neurological activities usually range between 4 to 20 Hz. The basic channels for which EEG signal can be categorized include alpha (7.5 – 14 Hz), theta (4 - 7.5 Hz), delta (0.5 - 4 Hz), beta (14 - 40 Hz) and gamma (> 40 Hz). The EEG is considered to be the most preferred non-invasive BCI (Brain Computer Interfacing) device due to its high temporal resolution, portability and cost effectiveness. A few general applications of the EEG involve in the evaluation of brain related disorders and also help assisting in cognitive related disorders.

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. This often happens in EEG due to its small amplitudes. These artifact generated noise can be of that generated by the electrode or by the participant. Some other types of noise include baseline movement, noise produced by Electromyogram (EMG) and Electrooculogram (EOG). In order to study the neurological activities of the brain more clearly, removal of noise is necessary. Various denoising methods has been proposed which includes Independent Component Analysis (ICA) method of denoising, Principle Component Analysis (PCA) method of denoising, wavelet based denoising, wavelet packet denoising to name a few. The performance measure of the above methods can be evaluated using Signal-To-Noise ratio (SNR), Peak-Signal-To-Noise ratio (PSNR) and Mean Square Error (MSE). The SNR value is supposed to have increased upto 19 dB as a result of decomposition of the signal into low pass component and high pass component using Wavelet Packet Transform. The removal of Ocular based artifacts can be calculated by using Wavelet based Threshold method and Principle Component Analysis (PCA) based adaptive threshold method [1].

2. EXISTING SYSTEMS
Some methods which are available in pursuit of artifact removal from the EEG signals include Linear Filtering, Linear Combination and Regression (LCR), Blind source separation (BSS) and Wavelet based denoising

2.1 Linear filtering based approach
This method could be defined as the most simple and practical approach for artifact removal that is present in a particular range of frequencies on the spectrum. The method is used to remove the ocular artifacts. In order to remove the artifact in the EEG it is required to clearly differentiate the frequencies pertaining to neurological activities and that of the artifacts. However this method becomes ineffective if there is any overlap of frequencies of neurological signal and that of the artifact generated signal. However, In order to reduce artifacts such as powerline noise or baseline noise in EEG, an Adaptive Least Mean Square (LMS) and Normalized Least Mean Square (NLMS) methods [2] could be used which is derived from the linear filtering process.

2.2 Linear combination and regression
The goal of the adaptive filter is to change the linear filter coefficients and its resulting frequency response in order to generate a signal that reflects the noise present in the signal to be filtered. The cost function is minimised in order to determine the filter coefficients.

When it comes to filtering EEG signal with that of EOG, This method also removes part of the EEG signal which is considered to be a drawback of this method. A general block diagram of the structure of an Adaptive filter is shown in fig.1.

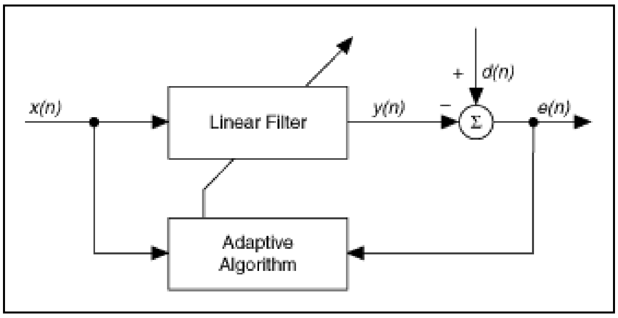


Fig 1: General block diagram of adaptive filter

The adaptive filter initially adjusts its coefficients to obtain a minimum squared error between the primary signal and its output. The LMS algorithm has fixed step size parameter for every iteration, In order to overcome this drawback a statistical understanding of the input signal is required before applying the LMS algorithm. However, the practicality of the above mentioned solution is quite questionable. By calculating the maximum step size value this problem could be bypassed, this is done by extending the LMS algorithm by applying normalization to Least Mean Square method (NLMS).

2.3 Recursive least square algorithm

The Recursive Least Square Filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals [3]. It is observed that there is an increase in SNR value compared to the other two algorithms mentioned above [3]. The RLS algorithm’s performance is at its best in time varying environments, but as a consequence increases the system complexity along with some stability problems.

2.4 Blind source separation methods

Blind source separation, is the segregation of a set of source signals from a set of mixed signals, without the help of information (or with very little information) about the source signals or the mixing process. This problem is in general highly underdetermined, but useful solutions can be derived under a surprising variety of conditions. Some methods defined under BSS are:

2.4.1 Principle component analysis

Principal component analysis (PCA) [4] is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components as shown in fig 2.

Berg et.al [5] reports that the PCA method outperforms that of the regression based methods. The principle components Analysis method is quite effective to remove the ocular effects from the EEG signal, but could not distinguish between eye blinking, ECG and EMG which has similar amplitudes [6].

To overcome this drawback a combination of Singular Value Decomposition (SVD) with PCA was performed [7], but it required the distribution of the source of the signal 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.

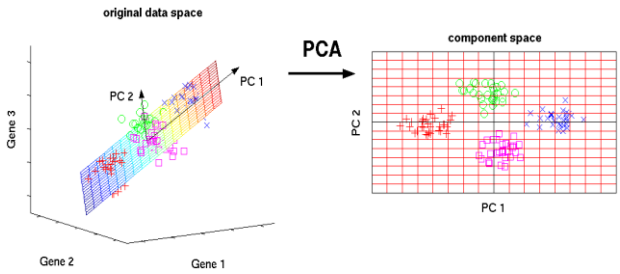


Fig 2: Principal Component Analysis

2.4.2 Independent component analysis method

The Independent Component Analysis (ICA) method along with performing good decorrelation to the signal also performs with signals having higher order statistical dependencies. As a result the EEG and EOG signals can be separated using this method [8] [9]. In general, with respect to EEG signal analysis, the method can be defined in eq.1,

$$x = W s \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where, x represents the EEG signal recorded from scalp, s represents the dipole source where the EEG is originated and W represents the linear mixing matrix.

Some common methods used by ICA for denoising EEG signals are:

1. Infomax (INFOrmation MAXimisation) Algorithm

Initially proposed by Bell and Sejnowski, this method separates the unknown source signals from a number of mixtures of signals, this is achieved by performing gradient ascent to the signals [10]. However this algorithm is efficient only for small number of signals.

To perform on more number of signals improvements on gradient ascent algorithm should be made in the Infomax algorithm [10]. In order to separate the sub Gaussian and super Gaussian source distributions an extension to the Infomax algorithm is proposed [11].

2. Extended Infomax

The Extended Infomax algorithm blindly separates the mixed signals containing sub Gaussian and super Gaussian source distributions. To implement this method, a simple type of learning is rule was derived by choosing a projection pursuit index considering the negentropy [11]. Parameterized probability distributions that have sub- Gaussian and super Gaussian regimes were used to derive a general learning rule that preserves the simple architecture proposed by Bell and Sejnowski [10], further optimization is performed using natural gradient, it also uses the stability analysis of Cardoso and Laheld [12] to switch between sub-Gaussian and super-Gaussian regimes. When this algorithm was used in high dimensional data from EEG recordings, it showed effectiveness at separating artifacts such as eyeblinks, line noise from weaker electrical signals [11].

3. Joint Approximation and Diagonalisation of Eigen Matrices (JADE)

The method was initially proposed by Cardoso and Souloumiac [12]. The joint diagonalisation was initially achieved by using an extended Jacobi technique, which consist of applying successive planar Givens rotation, each time to a pair of columns of the unitary diagonilizing matrix such that associated submatrix are as diagonal as possible.

According to the quantitative analysis of different techniques used for noise cancellation in EEG, It has been demonstrated that signal separation techniques such as JADE and Extended ICA algorithm were more effective than EOG subtraction and PCA method for removing ocular artifacts from EEG

4. Fast ICA

The Fast ICA method was invented by Aapo Hyvärinen at Helsinki University of Technology. This method as most ICA methods, seek an Orthogonal rotation of prewhitened data, by a fixed point iteration scheme, that maximises the measure of non Gaussianity of the rotated components.

A comparative analysis was procured as shown in table 1 between fastica and JADE [13] with respect to PSNR considering the dataset of:

(i) http://sccn.ucsd.edu/~arno/fam2data/publicly_available_EEG_data.html. The signals from here are contaminated with EOG. Data is sampled at a rate of 128 samples per second recorded from 32 electrodes at 1000Hz

(ii) http://www.filewatcher.com/b/ftp/ftp.ieee.org/uploads/press/rangayyan.0.0.html. Data was collected at a sampling rate of 1000Hz but noise free. These signals had to be artificially contaminated.

The PSNR is defined as the ratio of maximum possible power of a signal and power of a corrupting noise that affects the fidelity of the representation. It is defined as shown in eq.2

$$PSNR = 10 * \log_{10}\left(\frac{MAX^2}{MSE}\right) \quad \text{............... (2)}$$

Table 1: The PSNR values for 13 EEG signals [13]

Sl.no	PSNR for 13 EEG signals	
	Fast ICA	JADE
1	-18.0969	-18-0923
2	-20.3987	-20.3985
3	-18.9641	-18.9687
4.	-20.9309	-20.9263
5	-20.8309	-20.836
6	-17.3893	-17.3954
7	-19.7221	-19.7266
8	-16.2355	-16.241
9	-23.2477	-23.2453
10	-21.2434	-21.2404
11	-26.4025	-26.4042
12	-25.359	-25.3609
13	-16.9794	-16.974

A major drawback in these ICA techniques is that they are not *automated* (Automatic selection of thresholding) and they also require visual inspection of independent components for decision of their removal [14].

Nicolau et al [13] had proposed a method to address this issue of automated artifact removal by applying a specific application called the Temporal Decorrelation Source Separation (TDSEP). One of the advantages of TDSEP is that since the separation is based on correlation of sources, TDSEP can separate signals which have a Gaussian Amplitude distribution.

Some other drawbacks of ICA algorithms include:

1. The performance of the ICA methods are dependent on the size of the dataset, the performance is low for small datasets

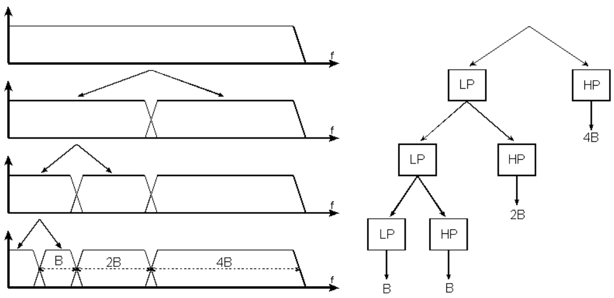
2.5 Wavelet based denoising method

Wavelet based analysis is used to functionally localize signals into time and frequency space. It is considered as a very effective technique for processing of non-stationary signals such as EEG signals. The wavelet transform decomposes the signal into wavelets by using wavelet functions called "mother" and "father" wavelet functions. It is possible to build a wavelet by any function by dilation of the mother wavelet function ψ(t), having a coefficient of 2^j, and transforming the resulting function with an interval proportional to 2^{-j} which can be defined as shown in eq.3,

$$\psi_{(a,b)}(t) = 2^{\frac{\alpha}{2}} \psi(2^{\alpha} t - b) \quad \text{.......... (3)}$$

The high frequency components correspond to the compressed version of the wavelet function and the low frequency components corresponds to the stretched version of the wavelet function. The details of the signal can be obtained by the correlation of the original signal and the wavelet function of different sizes. Multi resolution decomposition can be obtained by arranging the correlated wavelet functions in a hierarchical order. This multiresolution decomposition method separates the "details" at different moments of the signal and wavelet coefficients. These coefficients are known as *detail* coefficients and *approximate* coefficients which is implemented using low pass and high pass filters as shown in fig 3, and the transformation method is called as Discrete Wavelet Transform (DWT) [13].

The discrete details become smaller when there is an increase in the amplitude, however the coefficients of the useful signals will be retained to some extent.
Thresholding is done for the signals consisting of very small details which could be omitted. The two methods to denoising a signal in wavelet transform are soft thresholding and hard thresholding [13].



(a) (b)

Fig.3: a. the waveform representation, b. the decomposition of coefficients by low pass and high pass filters.

The Wavelet Packet Transform (WPT) divides the detail and approximation 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.
After compression-decomposition process for the EEG signals, the WPT method showed high robustness and low distortion for compression ratio in the range 5-8 [14], this method has a relatively low computation cost which makes it more appropriate towards practical applications.

A drawback observed in Wavelet based transformations is if the signal and the artifact have similar or higher values with respect to their amplitude, then wavelets have difficulty in distinguishing between them [13].

3. CONCLUSION

Considering the three general methods for the removal of artifacts in EEG signals which includes linear filtering, blind source separation methods and wavelet decomposition, each of these methods has its advantages and disadvantages.

The linear filtering though simple and practical becomes ineffective when encountered with signals with overlapping of frequencies pertaining to artifacts and the neurological activities.

We then could consider methods which does not imply on the information about the mixing process such as methods of blind source separation (BSS), In order to orthogonally build a set of linearly uncorrelated variables by considering a set of correlated variables we use the method of Principal Component Analysis (PCA), In the case of signals with higher order statistics we use the method of Independent Component Analysis (ICA), however, it's performance is very much dependent on the dataset.

A computationally effective way of processing non stationary signals includes methods of Wavelet based decomposition. But when there is situation of both signal and artifact having similar or higher value of amplitudes the wavelets have difficulty in distinguishing between them. But the ICA is considered to look inside the underlying conditions. By combining the methods of ICA and Wavelet transforms we could thus obtain a balance between computational effectiveness, practicality and higher order statistical information. Some important parameters such as power spectral estimation can be estimated by applying fast Fourier Transformations to wavelet decomposition methods.

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 denoising 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 deriving the linearity relationship between the sources. 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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