REMOVAL OF EYE-BLINK AND MOVEMENT ARTIFACTS FROM ELECTROENCEPHALOGRAPHIC SIGNALS

Kumar Kandukuri[#1], S.Abirami[*2], A.Aswini[*3], G.Vinothini[*4]
[#]*Assistant Professor, Department of Biomedical Engineering,*
Adhiyamaan College of Engineering, Hosur-635109, Tamilnadu.
[1]kandukuri.kumar@gmail.com
[*]*Final Year Students, Department of Biomedical Engineering,*
Adhiyamaan College of Engineering, Hosur-635109, Tamilnadu
[2]abiramisubramani12@gmail.com, [3]aswiniarunachalam77@gmail.com, [4]gd.vinothini@gmail.com

***Abstract*- In this modern world, Electroencephalographic signals (EEG) are veritably gaining attention as a origin of biometric information about the brain signals. EEG show versatility with individuals and has a definite spectrum. EEG may contain both physiological (muscle movement, eye movement and blink artifacts) and extraphysiological (AC and baseline wander) artifacts. Frequent intervene of Electrooculography (EOG) artifacts leads to serious problems in interpreting and analyzing the Electroencephalogram (EEG). This paper describes a robust method to eliminate eye-movement and eye blink artifacts from EEG signals using fixed point algorithm and support vector machine. Fast Independent Component Analysis (FastICA) is used to decompose EEG signals into independent components. The classification by feature-extraction methods are unsuitable for identifying eye-blink artifact components, hence a novel Peak Detection Algorithm of Independent Component (PDAIC) is used to identify eye-blink artifact components. Moreover, the features of topographies and power spectral densities of those components are extracted to identify eye-movement artifact components, and a Support Vector Machine (SVM) classifier is adopted because it has higher performance than several other classifiers. Finally, the artifact removal method proposed here is evaluated by comparing EEG data before and after artifact removal.**

***Keywords*- Independent component analysis (ICA), fastICA, support vector machine (SVM), Electrooculogram (EOG).**

I. INTRODUCTION

Electroencephalography is a domain concerning recording and interpretation of the EEG. Electroencephalogram (EEG) is a record of the electric signal generated by the cooperative action of brain cells, or more precisely, the time course of extracellular field potentials generated by their synchronous action. The amplitude of EEG of a normal subject in the awake state recorded with the scalp electrodes is 10–100 µV. In case of epilepsy, the EEG amplitudes may increase by almost an order of magnitude. In the cortex, amplitudes are in the range 500–1500 µV.

EEG signals are very much susceptible to artifacts and contain artifacts in the form of eye blink, eye movement, muscular movement, line noise, etc. Blinking of eye produces large electrical potential near the eye known as Electrooculogram (EOG). It is a non-cortical activity which contaminates the EEG while spreading across the scalp. Similarly, ECG signals may contain artifacts in the form of line noise, baseline wandering, tremor artifact, or any random unknown noise due to malfunction in electrodes.

These artifacts from EEG signals must be eliminated to increase the success rate of the system. The traditional ways of artifact removal which include visual inspection of artifacts, notch filters, etc., cannot effectively settle down the problem of filtering the overlapping signals. A new signal processing technique called Independent Component Analysis (ICA), based on multivariate signal analysis, emerged as a new and strange technique for decomposing the signals into several independent components. Fixed point iteration technique on signals will decompose into several independent components depending on statistical independencies of signals. The method of ICA can be applied to contaminate EEG signals to separate the noises from the useful signals.

II. LITERATURE REVIEW

Artifacts in EEG are commonly handled by discarding the affected segments of EEG. The simplest approach was to discard a fixed segment, perhaps one second, from the time where the artifact is detected. The recognition of eye blink and eye movement artifacts were generally effected by detecting a voltage increase in the EOG channel above a threshold of 100 µV. Other artifacts were manually marked and discarded. This can greatly decrease the amount of data available for analysis.

Some methods, based on regression of time/frequency domain, were suggested for removing artifacts [*Gratton et al. 1983*]. Moreover, some authors reported that the high frequency components of EOG may reflect the neural electric activity. Thus *Lins et al. (1993)* suggested that low pass filtering if EOG channel should be employed before applying the time-domain regression method. In fact, it is a controversial problem that influence of EOG artifacts on EEG is only low frequency range. Hence, Regression method may not be suitable for removing EOG artifacts.

In recent years, Blind Source Separation (BSS) methods have been used to remove the various artifacts of EEG signal [*Jung et al.2000, Joyce et al. 2004*]. This method recovers the unknown source signal S by introducing the Mixing matrix A.

The mixture is considered to be linear: X(t)=AS(t). By inversing the mixing matrix, we obtain the source signal: $S(t)=A^{-1}X(t)$.

More recently, multivariate statistical analysis techniques, such as Principal Component Analysis (PCA), have been used to separate and remove noise signals from the brain activity of interest. The PCA assumes that the signals are spatially and temporally uncorrelated.

Independent Component Analysis (ICA) is a method for finding underlying components within a mixture of signals which are both statistically independent and non-Gaussian from multivariate (multi-dimensional) statistical data [*Comon 1994, Bell and Sejnowski 1995, Makeig et al.1996*]. The ICA model closely resembles the BSS model.

III. METHODOLOGY

A. Data collection

Twenty healthy male volunteers with age ranging between 23-27 years participated in the study. EEG and EOG signals were recorded for every subject on a data acquisition system (BIOPAC-MP 36, Biopac Systems, Inc.) at a sampling rate of 256 Hz. Subjects were instructed to lie down on the bed with open eyes and relaxed state. EEG was recorded from Fp1 and Fp2 as an active electrode and C_Z as a reference electrode.

B. Fast Ica or fixed point algorithm

There are various measures of finding the non- Gaussianity such as Kurtosis and Negentropy. In this paper, we restrict ourselves to a novel and efficient method of Negentropy for the maximization of Non-Gaussianity by the principle of the FastICA algorithm.[6]

1) *Preprocessing by centering and whitening*

Centering is performed by making the model zero mean. The mathematical expression is given by,

$$x=x-E(x)$$

Whitening is performed to make variance equal to unit. The mathematical expression is given as follows:

$$E\{\hat{x}\hat{x}^T\}=I$$

Whitening reduces the number of parameters to be calculated and hence the complexity.

2) *Fast ICA for n units*

For estimating several independent components, the weights associated with components of **x** should be estimated**, i.e.** W_1, W_2 ...W_N, as independent sources. Following algorithm has been used for estimating W in iteration:[6]

1. Take an initial row vector *Wi*
2. Apply Newton phase

$$Wi = E\{\hat{x}g(Wi^T\ \hat{x})\} - E\{g'(Wi^T\ \hat{x})\}Wi$$

Whereas,

$$g_1(y)=\tanh(a_1 y)\,;\, g_2(y)=y^{*}e^{(-1/2y^2)}\,;$$
$$g_3(y)=4y^3$$

3. Normalization:
$$Wi=(Wi-mean)/std\cdot deviation$$
4. Decorrelation:
$$Wi=Wi-\sum Wi^T Wj\ \ Wj$$
5. Normalization again.
6. If *WT (i) *W(i −1) is not close enough to 1,* Let ***Wi+1*** *and go back to step 2*

C.Support Vector Machine

Support vector machines (SVMs) are build on developments in computational learning theory. Because of their accuracy and ability to deal with a large number of predictors, they have more attention in biomedical applications. The majority of the previous classifiers separate classes using hyperplanes that split the classes, using a flat plane, within the predictor space. SVMs broaden the concept of hyperplane separation to data that cannot be separated linearly, by mapping the predictors onto a new, higher-dimensional space in which they can be separated linearly[1].

The method's name derives from the support vectors, which are lists of the predictor values taken from cases that lie closest to the decision boundary separating the classes. It is practical to assume that these cases have the greatest impact on the location of the decision boundary. In fact, if they were removed they could have large effects on its location. Computationally, finding the best location for the decision plane is an optimization problem that makes uses of a kernel function to build linear boundaries through nonlinear transformations, or mappings, of the predictors. The intelligent component of the algorithm is that it locates a hyper plane in the predictor space which is stated in terms of the input vectors and dot products in the feature space. The dot product can then be used to find the distances between the vectors in this higher-dimensional space. A SVM locates the hyper plane that divides the support vectors without ever representing the space explicitly. As an alternative a kernel function is used that plays the role of the dot product in the feature space. The two classes can only be separated absolutely by a complex curve in the original space of the predictor.

The support vector classifier has many advantages. A unique global optimum for its parameters can be found using standard optimization software. Nonlinear boundaries can be used without much extra computational effort. Moreover, its performance is very competitive with other methods.

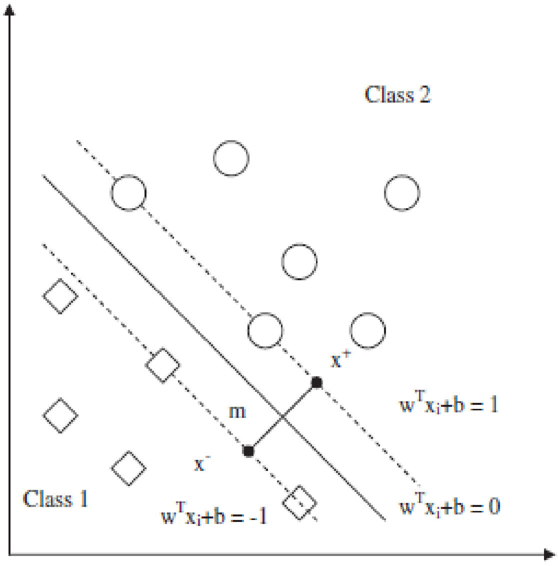

Fig 1: SVM classifier

IV. RESULTS

All the computations have been made in MATLAB R2009a (Propriety of Matrix laboratory). As explained in earlier sections, eye-blink and EEG signals are generated by different sources that are independent from each other. Thus, we can use FastICA to separate the signals, i.e. eyeblink artifact and EEG into statistically independent components. After the iterations using fixed point algorithm application of all, the desired artifact free signal has been obtained for further evaluation.

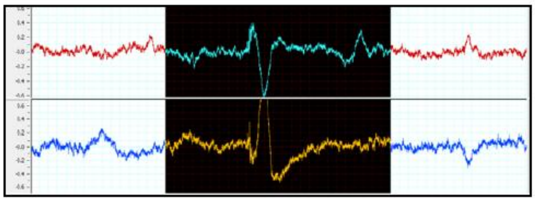

Fig 2: EEG signal with Eye Blink artifact recorded from BIOPAC

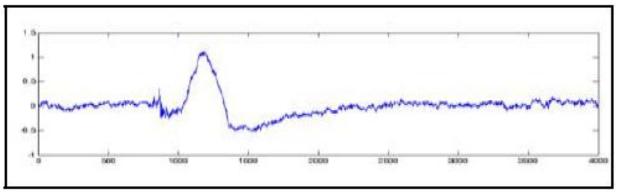

Fig 3: Portion of EEG contaminated with Blink artifacts

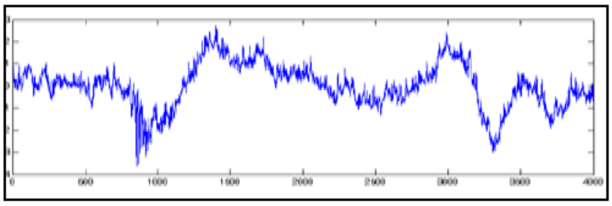

Fig 4: Artifact free EEG after FastICA application

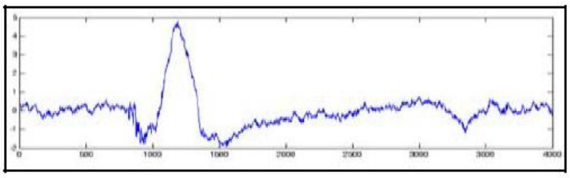

Fig 5: Eye Blink artifact separated out by FastICA

V. DISCUSSIONS/CONCLUSION

The ICA is a powerful tool for extracting the independent sources from the EEG signal mixed with artifacts using the concept that components are statistically independent. The ICA problem was formulated as the search for a linear transformation that minimizes the mutual information of the resulting components. FastICA is a fairly novel technique and found useful while being applied to the biomedical signal processing tasks. The efficacy of this algorithm has been proven with real EEG signal. This technique will lead to better results while interfacing it as a pre-processing step during biometric recognition. Later, SVM is used for extraction of other features in biomedical signals and classify the artifacts and pure signals. The results obtained in this process are very promising.

REFERENCES

1. Abdulhamit Subasi , M. Ismail Gursoy (2010) EEG signal classification using PCA, ICA, LDA and support vector machines Expert Systems with Applications journal homepage: www.elsevier.com/locate/eswa.
2. CARRIE A. JOYCE, IRINA F. GORODNITSKY, and MARTA KUTAS, Automatic removal of eye movement and blink artifacts from EEG data using blind component separation, Psychophysiology, 41 (2004), 313–325. Blackwell Publishing Inc.
3. A. Schlo¨ gl , C. Keinrath , D. Zimmermann , R. Scherer , R. Leeb , G. Pfurtscheller, A fully automated correction method of EOG artifacts in EEG recordings.
4. Seungjin Choi, Andrzej Cichocki, Hyung-Min Park and Soo-Young Lee Blind Source Separation and Independent Component Analysis:A Review.
5. Aapo Hyvärinen, Fast and Robust Fixed-Point Algorithms for Independent Component Analysis.
6. Puneet Mishra, Sunil Kumar Singla (2010) Artifact Removal from Biosignal using Fixed Point ICA Algorithm for Pre-processing in Biometric Recognition, measurement science review, volume 13, no. 1, 2013.

