International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 12 Issue 2 –JANUARY 2015.

EEG SIGNAL SEPARATION USING MULTIMODAL ANALYSIS FOR DIAGNOSTIC APPLICATION

#Gowri Priya N , *Ashmi Sabna V.Martina

#M.Tech, Biomedical Instrumentation, Karunya University, Coimbatore, India

**M.Tech, Biomedical Instrumentation, Karunya University, Coimbatore, India*

Abstract— **Electroencephalogram is a non-invasive record of brain electrical activity measured as changes in potential difference between pairs of electrodes placed on the human scalp. The electroencephalogram consists of a set of multi-channel signals including signals of activation of the head musculature, eye movements and interference from nearby electric devices. The measured EEG signals are the mixtures of underlying sources. In order to identify or detect some brain disorders, only the particular region (frontal/ parietal/occipital/temporal) signals are needed. This issue can be efficiently addressed through blind source separation techniques. Blind source separation is one of the promising approaches to retrieve their information from the mixed sources wherein the number and the mixing pattern of the sources are unknown. This paper shows how Blind source separation algorithms namely joint Independent Component Analysis (jICA) and Multi-set canonical correlation analysis (MCCA) together are used to separate the signals and remove artifacts from EEG signals. Through this proposed algorithm many datasets can be processed with high correlation coefficient. This advancement will help in biomedical signal processing techniques on electroencephalogram signals to be more widely used in the diagnosis of brain diseases such as epilepsy, Parkinson's disease, sleep disorders.**

Index Terms— **Electroencephalogram; joint Independent Component Analysis; Multi-set canonical correlation analysis; Parkinson's disease**.

I. INTRODUCTION

Electroencephalogram signal indicates the electrical activity of the brain. Electroencephalography is a non invasive technique used to diagnose brain related disease and symptoms. EEG signals are highly non-Gaussian, non stationary and have a non linear nature. So it is very difficult to get useful information from these signals. The signals are acquired from scalp at different regions using multiple electrodes. So the signals that are acquired from each electrode consists of mixed signals. The mixed sources should be separated in order to diagnose diseases. This can be done using technique called Blind Source Separation (BSS). Blind Source Separation is a technique used to separate the source signals from the mixed signals, without or with very little information about the original sources and the mixing process which is shown in Fig.1.

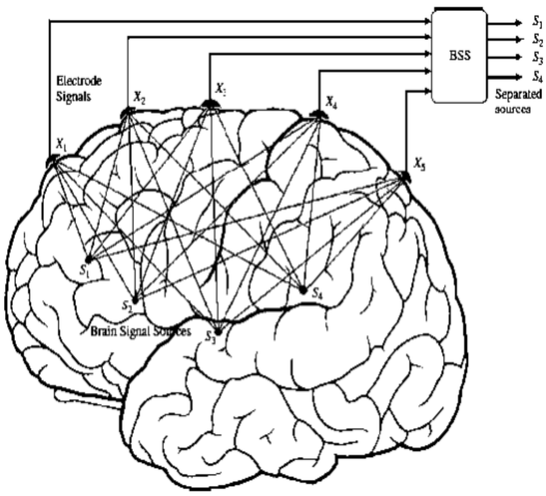
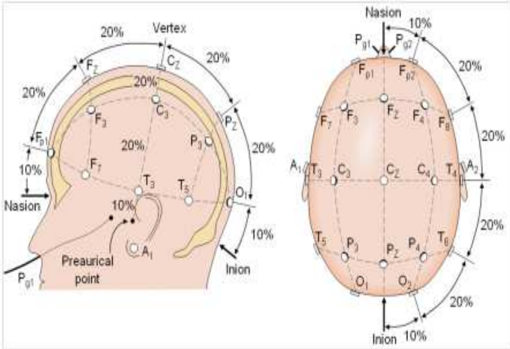


Fig .1 Blind Source Separation (BSS)

II ELECTRODE SYSTEM

EEG signals are usually acquired using superficial scalp electrodes, placed according to the 10-20 international system depicted in Fig. 2. The "10" and "20" refer to the percentage of the distance between the landmark points, namely the inion, the nasion, and the preaurical points namely the inion, the nasion, and the preaurical points, as shown in Fig. 2(a) and (b), used to draw the lines at which intersections the electrodes are positioned. In other words, given the landmark points, the electrodes positioning is made by considering the intersections between lines which are sagittally and coronally drawn, spaced at 10 or 20% of the distance between the landmark points. Since the early research on EEG analysis, it has been observed that the regions of a healthy human cortex have their own intrinsic rhythms in the range of 0.5 − 40Hz. In general, five main rhythms can be detected from an EEG recording: Delta (δ) 0.5−4Hz, Theta (θ) 4− 8Hz, Alpha (α)8 − 14Hz, Beta (β) 14 − 30Hz and Gamma (γ) over 30Hz.



(a) (b)

Fig.2 Electrode Placement

III METHODOLOGY

Blind Source Separation techniques are the most common and beneficial method in signal processing. The scope of the project is to separate the EEG source signals in order to increase the efficiency and accuracy of the diagnosing process. By applying blind source separation techniques the signals from each brain regions are separated, artifacts are removed and also the signals become more accurate and independent. In this paper joint Independent Component Analysis and Multiset Canonical Correlation are the two techniques which are combined together to separate the EEG source signals. The proposed blind source separation technique is used to remove noise [2] and separate the EEG source signal efficiently. Signals from four regions of brain are taken and the independent sources are separated using the proposed technique. The signal processing is done using software called MATLAB. The average correlation coefficients are determined in order to test the performance of the proposed method. The General Block Diagram is shown in the Fig 3.

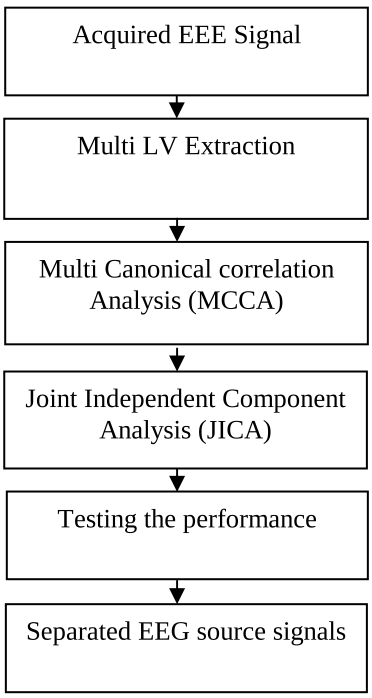


Fig.3 Block Diagram

IV.ALGORITHM IMPLEMENTATION

The EEG source signal separation involves three main steps namely,

1. Multi Latent Variable (LV) extraction
2. Multi Canonical correlation Analysis (MCCA)
3. Joint Independent Component Analysis (JICA)

A. Multi Latent Variable Extraction

Latent variables (or hidden variables), are variables that are not directly observed but are rather inferred (through a mathematical model) from other variables that are observed (directly measured). Suppose we have M datasets $X1$ (size $N \times P1$), $X2$ (size $N \times P2$), . . ., and XM (size $N \times PM$). All columns of the M data matrices are assumed to be zero-mean and normalized to unit variance in advance. The sublatent variables (subLVs) in each dataset is defined as linear combinations of the original variables, i.e., $X1w1$,$X2w2$, . . . ,$XMwM$. One super latent variable (supLV) tg is designed to relate the subLVs and it can be obtained by solving optimization problem.Multiple data sets are used so multiple LV's are extracted from the input signal. Thus the process is called as multi LV extraction. Latent variable extraction indirectly means the independent component selection in this paper.

B. Multiset Canonical Correlation Analysis

Canonical correlation analysis (CCA) is a way of measuring the linear relationship between two multidimensional variables [6]. It finds two bases, one for each variable, that are optimal with respect to correlations and at the same time, it finds the corresponding correlations. In other words, it finds the two bases in which the correlation matrix between the variables is diagonal and the correlations on the diagonal are maximized. The dimensionality of these new bases is equal to or less than the smallest dimensionality of the two variables. Canonical Correlation Analysis (CCA) is a well-known technique in multivariate statistical analysis, which has been widely used in economics, meteorology and in many modern information processing fields, such as communication theory, statistical signal processing and Blind Source Separation (BSS). Typically, CCA is formulated as a generalized eigen value (GEV) problem. However, a direct application of eigen decomposition techniques is often unsuitable for high dimensional data sets as well as for adaptive environments due to their high computational cost.

The advancement of CCA is the Multiset Canonical Correlation which correlates multiple data sets of EEG. The M-CCA can achieve excellent performance, especially when the datasets are large. It is more advantageous than CCA. In contrast to CCA where correlation between two canonical variates is maximized, M-CCA optimizes a objective function of the correlation matrix of the canonical variates from multiple random vectors such that the canonical variates achieve maximum overall correlation. Furthermore, due to the consideration of multiple random vectors, M-CCA cannot be solved by a simple eigenvalue decomposition problem as in the case of CCA. Instead, M-CCA takes multiple stages such that in each stage, one group of canonical variates are obtained by optimizing the objective function with respect to a set of transformation vectors. For the second stage and higher stages in M-CCA, the estimated canonical variates are constrained to be uncorrelated to the ones estimated in the previous stages. When M-CCA and CCA are applied to joint BSS on datasets, M-CCA has the advantage that the separability condition is relaxed as the number of datasets incorporated into the analysis is increased and correspondingly, the source separation performance is improved. This is observed in the results of the source separation experiments on simulated datasets.

The five objective functions of M-CCA algorithm are

1. Maximum of SSQCOR
2. Minimum of GENVAR
3. SUMCOR
4. MAXVAR
5. MINVAR

It is observed that M-CCA solutions using SSQCOR objective is robust for both homogeneous and heterogeneous correlation structures, real and complex valued data types, as well as complex circular and non-circular distributions. So SSQCOR has been used here.

Steps for implementing MCCA using matlab:

STEP 1: Load the input signal
STEP 2: Enter the number of samples
STEP 3: Implement the Cost functions 'genvar', 'maxvar', 'minvar', 'ssqcor'
STEP 4: Plot the signals using plot ()

The signals after MCCA are analyzed using joint independent component analysis

C. Joint Independent Component Analysis

Independent component analysis (ICA) [1] is a relatively recent method for blind source separation (BSS), which has shown to outperform the classical principal component analysis (PCA) in many applications. In particular, it has been applied for the extraction of ocular artifacts from the EEG, where principal PCA could not separate eye artifacts from brain signals, especially when they have comparable amplitudes ICA performs BSS of statistically independent sources, assuming linear mixing of the sources at the sensors, generally using techniques involving higher-order statistics. To extract the true independent, in Step 3, we perform jointICA on the concatenated CVs to minimize their higher order statistical dependencies We employed the jointICA implementation of the ICA . After the jointICA, the underlying sources $S1$, $S2$, . . ., Sm have been extracted from datasets $X1$, $X2$, . . ., Xm, with each column of S representing an individual source for the corresponding dataset. xj = aj1s1 + aj2s2 + .. + ajnsn, for all j **x** = **AS.** IC‘s **S** are latent variables & are unknown and Mixing matrix **A** is also unknown. Task is to estimate **A** and **S** using only the observeable random vector **x**. It is assumed that number of IC‘s is equal to number of observable mixtures and **A** is square and invertible. So after estimating A, can compute W=1/A and hence **s = Wx =1/AX** ICA decomposition is achieved by means of the jointICA algorithm. This algorithm maximises the non-gaussianity of the estimated component time courses, expressed in term of the negentropy of the component statistical distribution, an information theoretic function defined as the difference between the entropy of a Gaussian random variable with the same mean and variance and the entropy of component itself. Maximizing the non-gaussianity of the components is a fundamental criterion to achieve statistical independence between components. JointICA runs according to a deflation scheme that allows sequentially obtaining the channel weights (unmixing matrix), and hence retrieving the ICs. After each IC estimation, the variance explained by this component is regressed out from the data (decorrelation) and a new IC is estimated. The procedure is stopped when no convergence is possible after a given number of attempts and restarting from random weights. The signals are separated and the signal processing is done using MATLAB software.

Procedure for implementing Joint ica using matlab:

STEP 1: Load the input signal
STEP 2: Enter the number of samples
STEP 3: Multiply the input signal with mixing matrix
STEP 4: Use ICA function
STEP 5: Plot the signals using plot ()
STEP 6: Run the program

V RESULTS AND DISCUSSIONS

The proposed algorithm was successfully implemented using MATLAB software. The results were obtained by processing the EEG signal and the sources are separated. Initially the algorithm was tested using manually generated test signals (eg. sine, cosine). The test signals were first generated and mixed with mixing matrix (randomly generated) and then the original signal was separated from mixed signal after applying the proposed algorithm which were shown in Fig.4, Fig.5 and Fig.6. The algorithm was tested using EEG signals obtained from

1) Physionet
2) Raw EEG of patients from Hospital

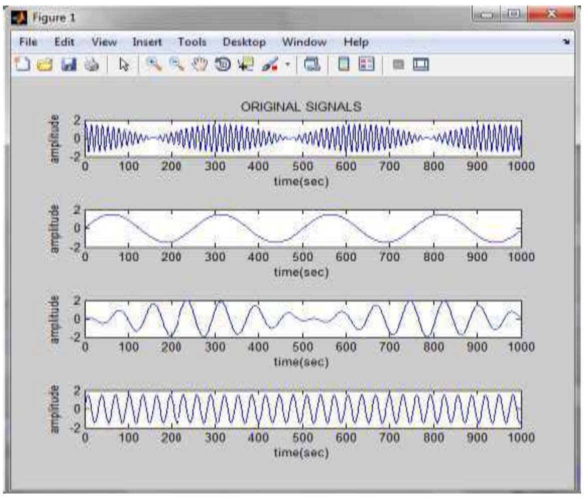


Fig.4 Original Test Signal

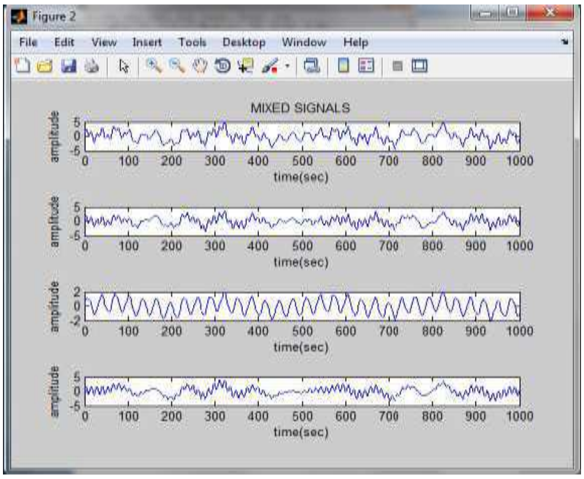


Fig.5 Mixing Signal for Test Signal

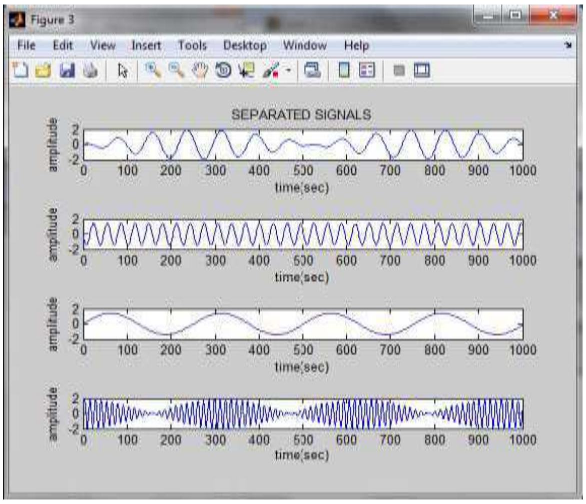


Fig.6 Separated Test Signal

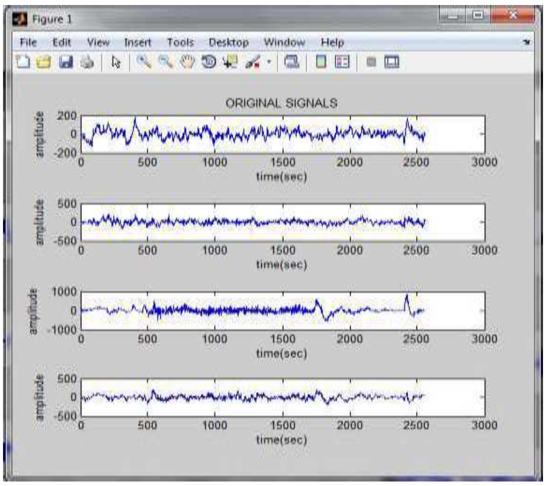


Fig.7 Original Physionet EEG Signal

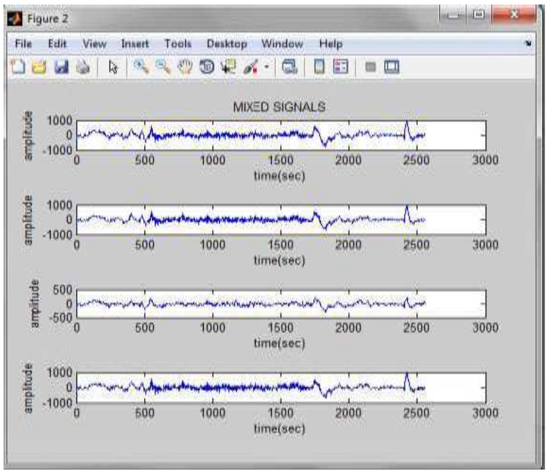


Fig.8 Mixing signal for Physionet EEG Signal

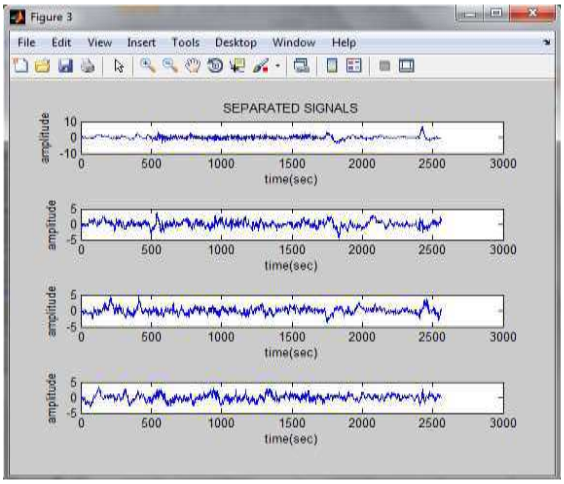


Fig.9 Separated Physionet EEG Signal

EEG signal data is taken from four brain regions of the patients namely Frontal, Parietal, Ocipital and Temporal regions. The data is mixed with mixing matrix and then proposed algorithm is applied and thus mixed signals are found and signals are separated.

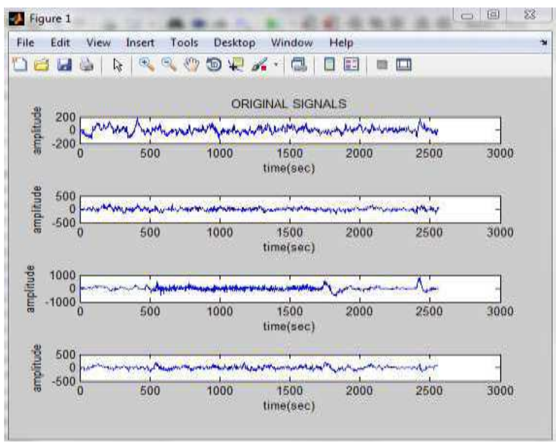


Fig.10 Original Raw EEG Signal from Patient

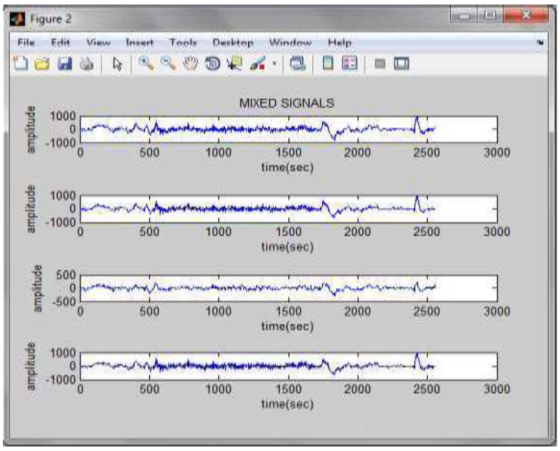


Fig.11 Mixing signal for Raw EEG Signal from Patient

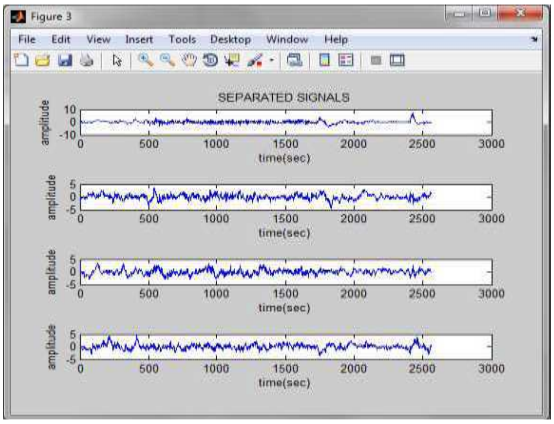


Fig.12 Separated Raw EEG Signal from Patient

The performance of the algorithm was estimated using average cross correlation coefficient between the original and separated signal. The Table.1 shows the Average Cross Correlation Coefficient (ACCC) that was obtained for the proposed algorithm.

Table.1 Average Cross Correlation Coefficient

S.No	Method	ACCC for		
		Test signal	Physionet EEG signal	Raw EEG signal
1	ICA	0.8721	0.7398	0.8392
2	MCCA	0.8701	0.8587	0.8566
3	PROPOSED METHOD	0.8913	0.8725	0.8853

VI CONCLUSION AND FUTURE WORK

The proposed method combines the advantages of the Multi Canonical Correlation Analysis and Joint Independent Analysis. The simulation results support the usefulness of the proposed method. The performance and efficiency was good and well understood from the average correlation coefficient that was obtained by this method. The Artifacts were also removed in EEG signals through this algorithm. The proposed framework will be a promising tool for multi subject and multimodal data analysis. It was clearly understood that the proposed joint blind source separation scheme outperforms existing group analysis methods for large number of datasets and heterogeneous source correlation values. In other words, the proposed method is easier to achieve blind source separation than conventional method on a smaller group of datasets.

The proposed work can be applied for analysis of functional magnetic resonance imaging (fMRI) data from multiple subjects and show its utility in estimating meaningful brain activations. The algorithm can be applied for Electromyogram signal also.

ACKNOWLEDGEMENT

The author thanks **Prof. K. RAJASEKARAN,** Professor and Head, Department of Electronics and Instrumentation Engineering, Karunya University for encouragement in course of this work. The author also thanks **Mrs. SMILY JEYA JOTHI E**, Assistant Professor, **Mr. SAMSON ISAAC**, Assistant Professor for their exhilarating supervision, timely suggestion and guidance during all phase of this work. F.A thanks **Mr. R.JEGAN** , Assistant Professor for his help and also **Dr. S.THOMAS GEORGE**, Assistant Professor, EEE Department for providing the source signal.

REFERENCES

[1]. Bogdan, Mijovic, Maarten De Vos, Ivan Gligorijevic, (2010) "Source Separation From Single-Channel Recordings by Combining Empirical-Mode Decomposition and Independent Component Analysis", IEEE Transactions on Biomedical Engineering, vol.57, pp:2188-2196.

[2]. Garrick L. Wallstrom, Robert E. Kass, Anita Miller, (2004) "Automatic correction of ocular artifacts in the EEG: a comparison of regression-based and component-based methods", International Journal of Psychophysiology, vol.5, pp:105-119.

[3] .Hua-Gang Yu, et al., (2010) "Nonlinear Blind Source Separation Using Kernel Multi-set Canonical Correlation Analysis", I.J. Computer Network and Information Security, vol.1, pp:1-8.

[4]. Kaiquan Shen, et al., (2013) "Multiple Time-Lag Canonical Correlation Analysis for Removing Muscular Artifacts in EEG", International Conference of the IEEE EMBS, pp:6712-6716.

[5]. Kim, H. T. Attias, S. Y. Lee, and T. W. Lee, (2007) "Blind source separation exploiting higher-order frequency dependencies," IEEE Transaction on Acoustic Speech Signal Process, vol.15, pp: 70-79.

[6]. Liu . W, D. P. Mandic, and A. Cichocki, (2007) "Analysis and online realization of the CCA approach for blind source separation," IEEE Transaction on Neural Network, vol.18, pp:1505–10.

[7] .Manoj Kumar Mukul, Fumitoshi Matsuno, (2011) "EEG Filtering based on BSS Algorithm and Its Modification for BCI", Proceedings of 8th Asian Control Conference, pp:880- 886.

[8]. Rabeya Ferdousy, Md. Afzalur Rab, (2010) "Electrooculographic and Electromyographic Artifacts Removal from EEG", International Conference on Chemical, Biological and Environmental Engineering, pp:163-167.

[9]. Ricardo Vigário, Jaakko, Veikko Jousmaki, (2000) "Independent Component Approach to the Analysis of EEG and MEG Recordings", IEEE Transactions on Biomedical Engineering, vol.47, pp:589-593.

[10]. Vigario R. N, (1997) "Extraction of ocular artifacts from EEG using independent component analysis", Electroencephalography And Clinical Neurophysiology, vol. 103, pp:395-404.