D.Kumar swamy,K.Srinivasa Reddy/ International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 2, Issue 6, November- December 2012, pp.1405-1408

System performances in recovery of EEG Signals using Modern-Fast-ICA

D.Kumar swamy,K.Srinivasa Reddy
(M.Tech,S.R Engineering College
(Associate professor, S.R Engineering College

ABSTRACT:

Electroencephalogram (EEG) is used for the analysis of brain signals obtained from various electrodes placed across the scalp at specific positions. The collected signals from brain are oftenly contaminated with Ocular Artifacts(OAs), EKG and EMG artifacts. In this project a novel technique is used for the removal of ocular artifacts using Modern-Fast-ICA algorithm which decomposes the EEG signals into independent components then an LMS(Least Mean Squares)based adaptive algorithm is applied to the independent components so as to get the original EEG signals. In the first step,independent basis functions attributed to OA are computed using Modern-FastICA algorithm. In the second step we arrive ocular artifact free EEG signal efficiently comparative to Modern-Fast-ICA. In this paper, based on some parameters like Root Mean Square Deviation(RMSD) we can say that the EEG signal obtained after second step is better than after the first.

***Keywords*-**EEG,Electrooculogram, adaptive filters,Artifact rejection, Fast independent component analysis.

I.Introduction:

One of the most developing researches in Engineering that utilizes the extensive research in medicine is Biomedical Engineering. This area seeks to help and improve our everyday life by applying engineering and medical knowledge with the growing power of computers. The computers are efficient, straightforward and never get tired or sick, while humans though are smart and creative, become sick, weak and limited. Communication between humans seem usually much simple than the one involves humans and machines. This difficulty increases when a person is disabled. However, especially this kind of people has more to gain by assisting a machine in their everyday life. Aim of this project is to separate (EOG) and Electroencephalogram (EEG) signals as they are having the problem of interfering each other while recording with electrode placement mechanism. I have used Blind Source Separation for separate the mixed signals by taking EEG & EOG signals from MIT-BIH data from net and these signals are mixed to get two mixers with some mixing process. For these two mixers the BSS algorithm is applied and separated successfully. Skeletal muscle fibers are twitch fibers: produce a mechanical twitch response for a single stimulus and generate a propagated action potential. Skeletal muscles made up of collections of motor units (MUs), each of which consists of an anterior horn cell, or motoneuron or motor neuron, its axon, and all muscle fibers innervated by that axon.

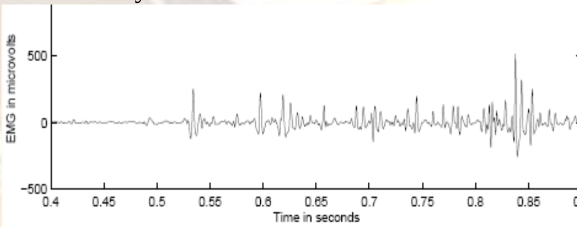

Fig1: The Electromyogram (EMG)

EEG or brain waves: electrical activity of the brain. Main parts of the brain: cerebrum, cerebellum, brain stem (midbrain, pons medulla, reticular formation), thalamus (between the midbrain and the hemispheres).

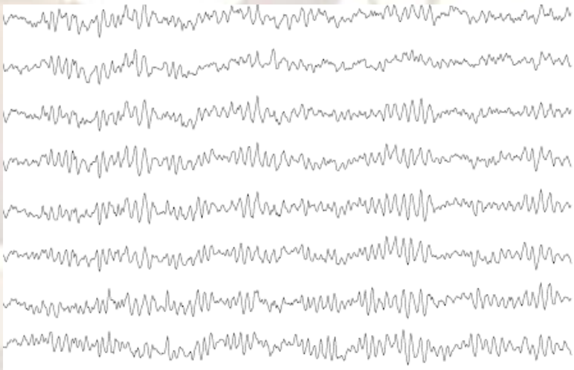

Fig2:The Electroencephalogram (EEG)

The electro-oculo graphy (EOG) is a measurement of bio potentials produced by changes in eye position. The fact that electrical activity could be recorded by placing electrodes on the surface of the skin in the eye region was discovered in the 1920's. It was realized that the electrical potentials induced corresponded (almost linearly) to eye movement. Originally, it was thought that the induced electrical activity caused by eye movement corresponded to the action potentials in the above mentioned pairs of muscles.

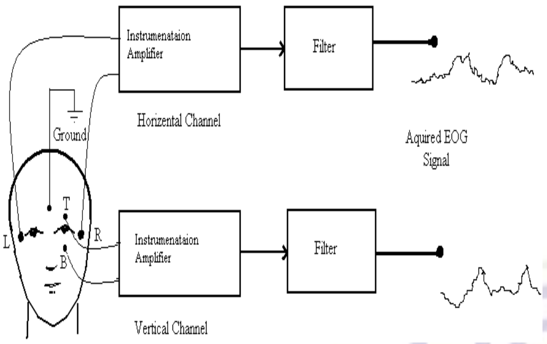

Fig3:collection of EEG signal

In this paper first we have taken the EEG signal contaminated with EOG. By using two mixers with some mixing process mix the both signals to become an interfering signal. Modern fastICA is applied to the mixture components to separate the independent components.i.e EEG signal and EOG signal.

Second step we have used Least Mean Square(LMS) algorithm to again purify the EEG signal obtained.

This paper follows II.Methods used,III.Results obtained,IV.Acknowledgement,V.Conclusion and finally VI.References.

II.Methods used: Independent component analysis

(ICA) is a well-known method of finding latent structure in data. ICA is a statistical method that expresses a set of multidimensional observations as a combination of unknown latent variables. These underlying latent variables are called sources or independent components and they are assumed to be statistically independent of each other. The ICA model is

$$X = f(\theta, s) \qquad ....(4.1)$$

Where $X = (X_1, ..., X_m)$ is an observed vector and f is a general unknown function with parameters θ that operates on statistically independent latent variables listed in the vector $s = (s_1, ..., s_n)$. A special case of (2.1) is obtained when the function is linear, and we can write

x = As . ...(4.2)

Where A is an unknown m×n mixing matrix. In Formulae (2.1) and (2.2) we consider x and s as random vectors. When a sample of observations $X = (x_1, ..., x_n)$ becomes available, we write X = AS where the matrix X has observations x as its columns and similarly the matrix S has latent variable vectors s as its columns. The mixing matrix A is constant for all observations.

The ModernFasICA algorithm is described below:

1. Center the data to make its mean zero, then whiten the result to get X.
2. According to the formula $\frac{d_1 + d_2 + d_3 + .. d_m}{d_1 + d_2 + d_3 + .. d_n} = 98\%$, choose m eigen vectors, then whiten the data to get Z using formula

$$z = D^{-1/2} E^T$$

3. Initial the separate matrix W, for every $w_i, i = 1, ..., m$ unit of norm. Orthogonalise matrix W as in step 5.
4. For all $w_i, i = 1, ..., m$. Let

$$w_i \leftarrow E\{zg(w_i^T z)\} - E\{g^T(w_i^T z)\} w_i$$

To renew w_i generally we chose **g(.)** as hyperbolic tangent function.
5. Do a symmetric orthogonalisation of the matrix $W = (w_{1,} .... w_m)^T$ by $W \leftarrow (WW^T)^{-1/2} W$ or by the iterative algorithm.
6. Iterate between step 4 and step 5, stop if convergence is attained.

Symmetric orthogonalisation is done by first doing the iterative step of the one-unit algorithm on every vector $w_{i,}$ in parallel, then orthogonalise all the $w_{i,}$ by special symmetric methods. After all the iterations W can separate the observed signal into independent source components and mixing matrix A. $(A \square W^{-1})$

$$g(y) = \tanh(\alpha y) \text{ and}$$

$$g^T(y) = \alpha(\tanh^2(\alpha y))$$

where $1 \le \alpha \le 2$

LMS Adaptive algorithm:

.

1. Initially, set each weight $w_k(i), i = 0, 1, ..., N-1,$ to an aribitrary fixed value , such as 0.
For each subsequent sampling instant, $k = 1, 2, ...,$ carry out steps (2) to (4) given below.
2. Compute the filter output

$$\hat{n}_k = \sum_{i=0}^{N-1} w_k(i) x_{k-i}$$

3. Compute the error estimate

If both the original sources S and the way the sources were mixed are all unknown, and only mixed signals or mixtures X can be measured and observed, then the estimation of A and S is known as blind source separation (BSS) problem.

Results:

Fast ICA		LMS Adaptive Filter	
RMSD	8.017db	RMSD	20.3924db

Table1:performance measure

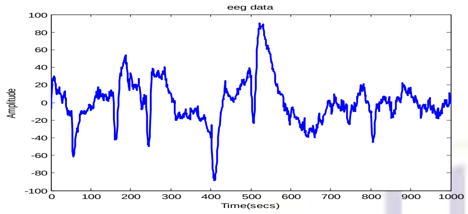

Fig4: EEG data signal

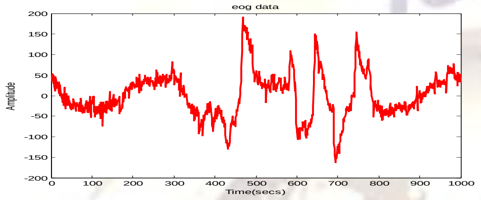

Fig5: EEG data signal

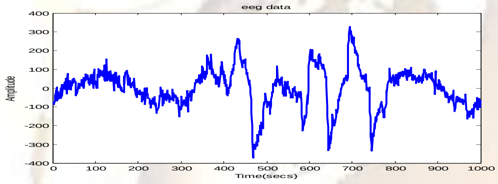

Fig6 :Mixed signal1

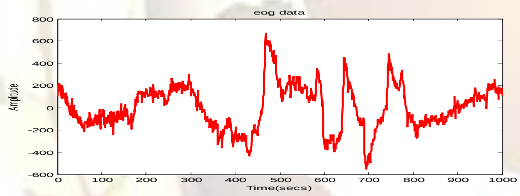

Fig7 :Mixed signal2

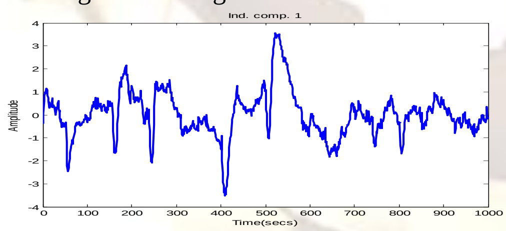

Fig8: Independent component1

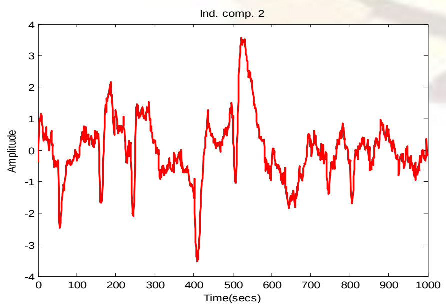

Fig9: Independent component2

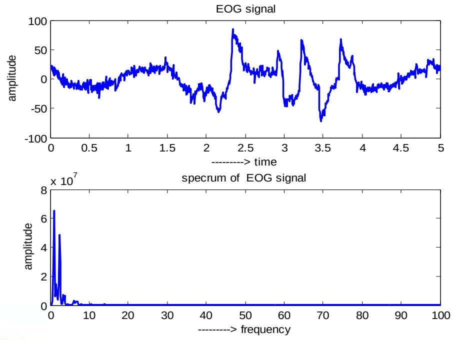

Fig10: Frequency spectrum of EOG signal

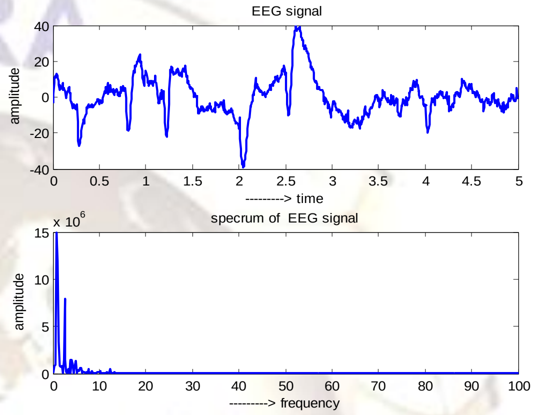

Fig11: Frequency spectrum of EEG signal

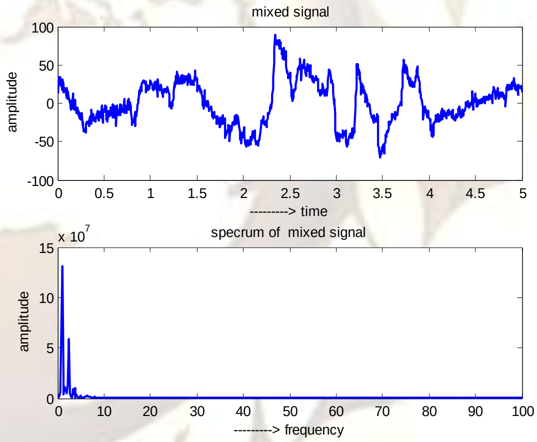

Fig12:Frequency spectrum of mixed signal

IV. Acknowledgement

I am grateful to to my guide sri.K.Srinivasa Reddy,Associate professor for helping me out to complete this project.

V. Conclusion:

The results shows that EOG signals can be easily eliminated using the robust technique that is used in this paper.

References

[1]. Rangaraj M .Rangayyan. ENEL 563 Biomedical signal analysis,IEEE/Wiley,New York,NY,2002

[2]. Comon P.1994.Independent component analysis, a new concept?Signal processing .36,287-314

[3]. Bell AJ and Sejnowski TJ.1995.An information –maximization approch to blind separation and blind deconvolution. Neural Computation,MIT Press.7,1129-1159.

[4]. Making S,Bell AJ, Jung T-P and Sejnowski TJ .1996.Independent Component Analysis of Electroencephalgraph- icData.Advance in Neural Information Processing Systems 8,MIT press,Cambridge MA.145-151.

[5]. Lee T-W.1998. Independent Component Analysis. Theory and Applications. Kluwer Academic publishers Hingham,M A,USA.

[6]. Hyvarinen A and Oja E.2000. Independent Component Analysis : Algorithms and applications. Neural Networks.13(2000),411-430.

[7]. Vigario R ,Sarela J,Jousmaki V,Hamlainen M,and Oja E.2000.Independent Component approch to the analysis of EEG and MEG recordings.trans.Biomed.eng.47,589-593.