Removal of Ocular Artifacts from EEG Signal using Joint Approximate Diagonalization of Eigen Matrices (JADE) and Wavelet Transform

Kali vara prasad Naraharisetti

Abstract -- *It becomes really hard to analize the Electroencephalogram signal (EEG) when it is corrupted by the eye movements and the eye blinks. This paper gives a strong background of removing the ocular artifacts (OA) from the EEG recorded at the scalp, by utilizing two methods namely Wavelet Transform and Joint Approximate Diagonalization of Eigen Matrices (JADE).*

Key Words -- Electroencephalogram (EEG), Electrooculogram (EOG), Symlet wavelet, Joint approximate orthogonalization of eigen matrices (JADE), Independent component analysis (ICA),Stationary wavelet transform (SWT), Discrete wavelet transform (DWT)

I . Introduction

The electrical activity on the brain is recorded by electroencephalogram (EEG) through the electrodes placed on the scalp of a person [7].The eye movements and eye blinks mostly contaminate the EEG signal. There are lot of variations in the EEG signal in terms of shape, frequency, amplitude. If the amplitude of EEG signal is below 20 µV ,then it is considered as low, if the amplitude is between 20 µV-50 µV,its considered as medium and if amplitude is above 50 µV then its considered as high [7].When human eye blinks or moves ,there is an electric field created which is two orders of magnitude greater than the desired electrical activity [7]. The EEG signal is distorted and masked by the electric field which propagates across the scalp [7]. "An eyeblink can last up to 400 ms and can be 10 times larger in amplitude than electrical signals originating from cerebral cortex [7]." EOG is defined as the electrical activity associated with the eye movement [7].

The placement of gold cup electrodes is based on 10-20 international system which says that the distance between the adjacent electrodes is 10% or 20 % of the total distance on the scalp. There were several methods which were brought up by several authors in order to remove the ocular artifacts from EEG. G.Wilson came up with the method of adaptive filtering using RLS algorithm in order to remove artifacts which are embedded in the EEG signal [15]. Rebeca Romo-Vazquez applied a method which was a combination of independent component analysis(ICA) and wavelet denoising in order to remove the ocular artifacts from EEG [11].

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V.Krishnaveni proposed wavlet transform to automatically identify and remove ocular artifacts from EEG [2]. P.Senthil Kumar combined adaptive technique using Recursive Least Square algorithm and wavelet transform to get correct the ocular artifacts without removing the underlying EEG information [14]. The focus of this paper is to detect the artifacts and remove them in order to have a clean study of EEG.

In order to remove the ocular artifacts, two techniques have been utilized namely joint approximate diagonalization of eigen matrices (JADE) and wavelet transform.

II. Algorithms

Independent component analysis (ICA):

Independent component analysis has few assumptions: (1) the input source signals are independent, (2) the mixing medium propagation delays are negligible, (3) the number of sensors is equal to the number of independent source signals. For example, if there are *N* sensors employed, by implementing ICA one can separate *N* sources [5]. Assumption 3 is some what questionable [5], since one is not sure how many independent brain signals are contributing to the EEG recorded on the scalp using the electrodes. Therefore, the output of ICA might be questionable. But, ICA still proves to be useful in this case[5].

The mixing ICA model can be represented as

$$x = As \qquad (1)$$

where x is given as N-dimensional vector consisting of the mixed signals x=$[x_1(\mathrm{k}), \ldots\ x_m(\mathrm{k})]^T$and s is an N-dimensional vector consisting of the independent source signals s = $[s_1(\mathrm{k}), \ldots\ s_n(\mathrm{k})]^T$ [11]. A is the unknown mixing matrix of size *m* by *n*. In order to save some computational costs , some preprocessing of input data is done [12].

Centering: Centering is removing the mean from each source [12]. If x has to be centered , remove the mean of x from x i.e., x – mean(x) [12].

Whitening: Whitening can be described as follows

$$J=Hx \qquad (2)$$

$$C_x = E\{x\, x^T\}=EDE^T \qquad (3)$$

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

Where E = (e_1 ,….., e_n) = orthogonal matrix of eigen vectors of C_x and D = diag(λ_1….λ_n) is diagonal matrix of eigen values of C_x

x is a zero mean vector and the covariance matrix C_x is given by the above equation.

H is called the whitening matrix and J is a new matrix which is white. Whitening is done to make the mixed signals uncorrelated .The aim of ICA lies in finding a linear transformation W such that the output signals are as independent as possible [11].

$$y = Wx = WAs \tag{4}$$

Where y consists of the estimated independent source signals, y = $[y_1(k), ...\ y_n(k)]^T$.When W becomes the inverse of A, the sources are recovered [11].There are many methods to the problem of ICA such as joint approximate diagonalization of eigen matrices (JADE).

Joint Approximate Diagonalization of Eigen matrices (JADE):

Joint approximate diagonalization of eigen matrices (JADE) is based on diagonalization of cumulant matrices [5]. Cumulant for random variables x_1, x_2 is given by

$$\text{Cum} (x_1 , x_2) = E [\overline{x_1}\, \overline{x_2}] \tag{5}$$

$$\text{where } \overline{x_i} = (x_i - E[x_i]) \tag{6}$$

A cumulant which has two different random variables is named as cross cumulant [16]. Equation 3 can be viewed as diagonalization because the eigen vectors are diagonalizing the covariance matrix to give a diagonal matrix. In case of JADE the matrix W diagonalizes F(M) for any i.e., WF(M) W^T is diagonal. Matrix F is a linear combination of terms of the form $w_i w_i^T$. w is a column of W. WF(M_i) W^T is made as diagonal as possible for different combination of M_i and i=1,…,k. The diagonality of matrix Q = WF(M_i) W^T can be measured as the sum of the squares of off-diagonal elements: $\sum_{k\neq l} q_{kl}^2$. Minimization of sum of squares of off- diagonal elements is same as maximization of sum of squares of diagonal elements [1].

$$J_{JADE}\,(W) = \sum_i \|\text{diag}(\ WF(M_i)W^T\ )\|^2 \tag{7}$$

Joint approximate diagonalization of F(M_i) can be obtained by maximizing J_{JADE}. Choice of the matrix M_i would be to take the eigenmatrices of the cumulant [1].After algebraic manipulations, the above equation becomes[1]

$$J_{JADE}\,(W) = \sum_{ijkl\neq iikl} \text{cum}(y_i, y_j, y_k, y_l)^2 \tag{8}$$

When the above equation is minimized the sum of squares of cross-cumulants of y_i is also minimized [1].

Wavelet Transform:

Wavelet transform is one of the finest techniques to analyze the EEG signals[2]. To understand the behavior of a signal wavelet transform transforms the signal into time and frequency localization i.e., wavelet can keep track of time and frequency [2].

In discrete wavelet transform , the wavelets are discretely sampled and it keeps track of frequency and local information . In DWT, this paper chooses scales *i* and positions *j* of the mother wavelet $\Psi(t)$ [2]

$\Psi_{i,j}(t) = 2^{i/2}\ \Psi\ (\ 2^i t - k)$ where i ,k are integers

Scales and positions chosen based on powers of two are named as dyadic scales and positions. “A wavelet can be built for any function by dilating a function Ψ (*t*) with a coefficient 2^i and translating the resulting function on a grid whose interval whose interval is proportional to 2^{-i}[2]”. The stretched versions of the wavelet function which are called dilated match the low frequency components and the compressed versions which are called contracted match the high frequency components [2]. Signal is separated into “detail” and “approximation” using the multi-resolution decomposition algorithm[2].

In stationary wavelet transform(SWT), the filters are upsampled at each level of decomposition and the signals are not subsampled. Due to subsampling operations, DWT does not preserve translation invariance which means - translation of signal does not imply translation of wavelet coefficients.But, SWT preserves this property[9]. SWT is shown in the figure 1.

Methodology for Wavelet transform [2]:

1) Stationary wavelet transform (SWT) is applied to the contaminated EEG signal (EEG with eye artifacts) with Symlet wavelet of order 3 being used and the EEG signal is decomposed into eight levels.

2) The eye blink artifacts should be identified.

3) Setup a threshold value and a threshold function for the ocular artifacts.

4) To reconstruct the EEG signal, apply wavelet reconstruction procedure.

Threshold function : Hard

Threshold value was selected based on rigrsure which is based on stein’s unbiased estimate of risk “One gets an estimate of the risk for a particular threshold value *t*. Minimizing the risks in *t* gives a selection of the threshold value[10]”.

The threshold function used in Hard is as follows [2]:

If wavelet coefficient value > threshold value

Then

new wavelet coefficient value = (-0.7)×(wavelet coefficient value)

else

new wavelet coefficient value = (old) wavelet coefficient value

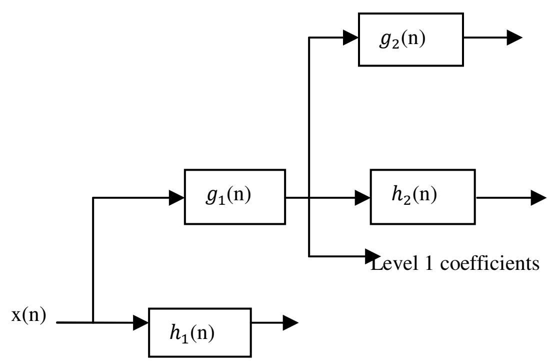

Fig. 1. Stationary wavelet transform [8]

III. Experimental Setup

The EEG signals were obtained using the CleveLabs BioRadio 150 which is a wireless lightweight programmable monitor for viewing and recording the brain signals. International 10-20 system was followed in order to get the EEG signals using the gold cup electrodes being placed at positions fp1, fp2, O1, O2. The following figure shows the 10-20 system.

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Figures (5), (6), (7), (8) show the artifact free EEG signal in red color and the contaminated EEG in blue color. In both the cases artifacts have been removed. When light is focused on their power spectral density plots in case of figure (7) & (8), it can be seen in figure (7) that there is a decrease in the power of low and high frequency components in case of JADE algorithm. In case of figure (8), the amplitude of ocular artifacts have been minimized, but phase and magnitude of the high frequency background EEG activity has been preserved. There is a decrease in the power of low frequency components while retaining the power of high frequency components.

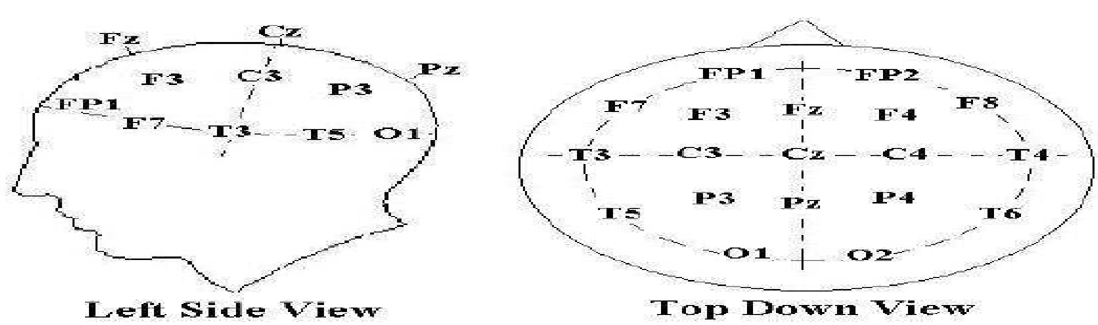

Fig. 2. International 10-20 System [17]

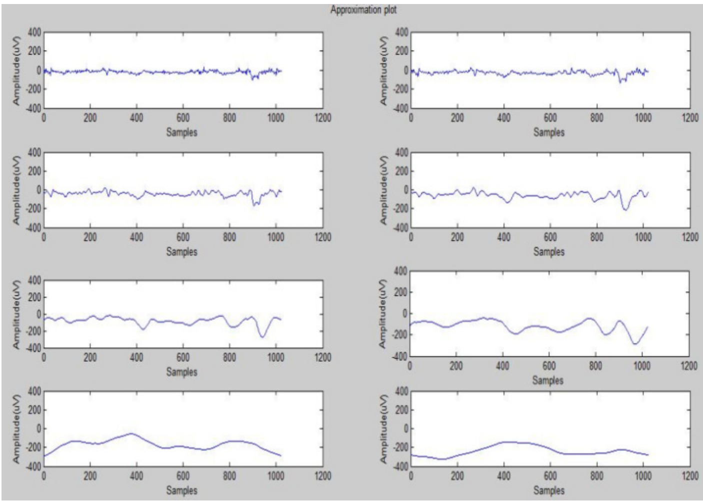

Fig. 3. Approximate plot

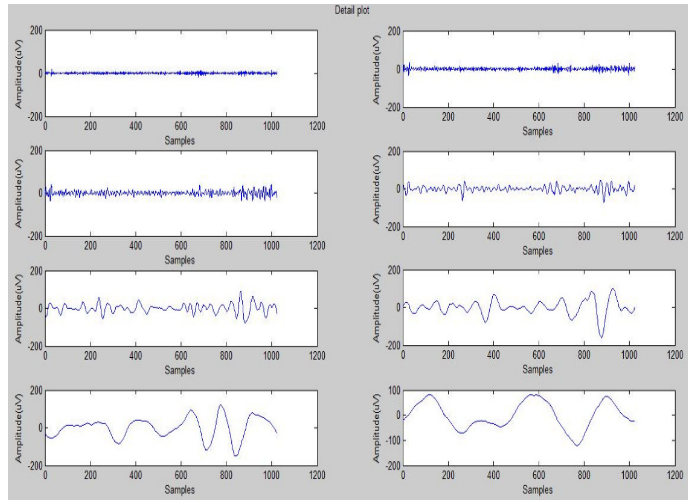

Fig. 4. Detail plot

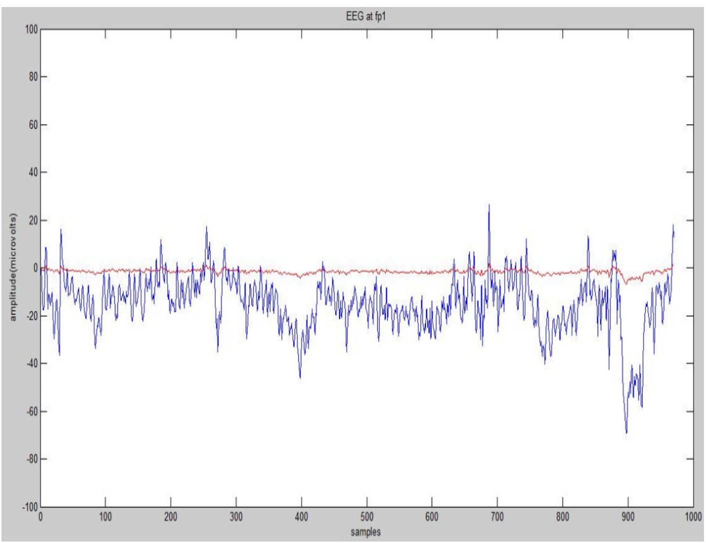

Fig. 5. Output EEG signal using JADE algorithm.

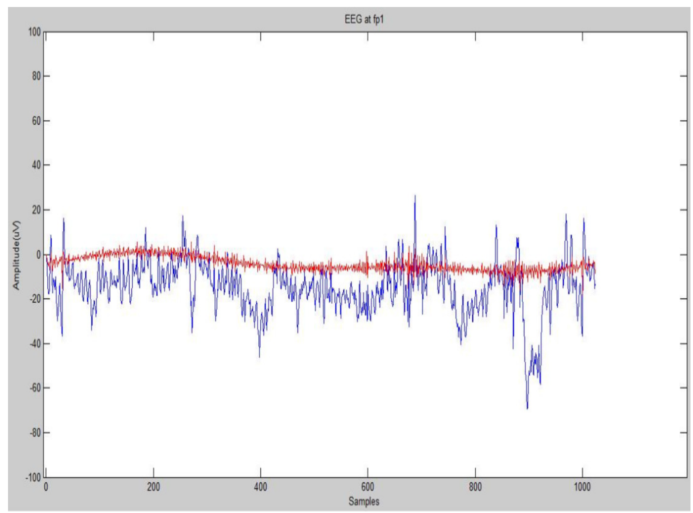

Fig. 6. Output EEG signal using wavelet transfom

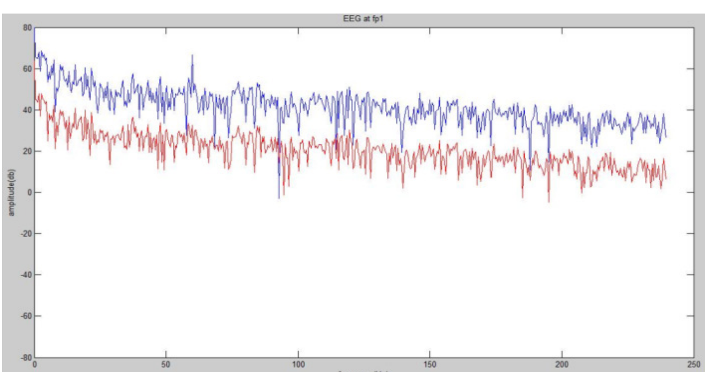

Fig. 7. PSD plot of output EEG signal given by JADE algorithm

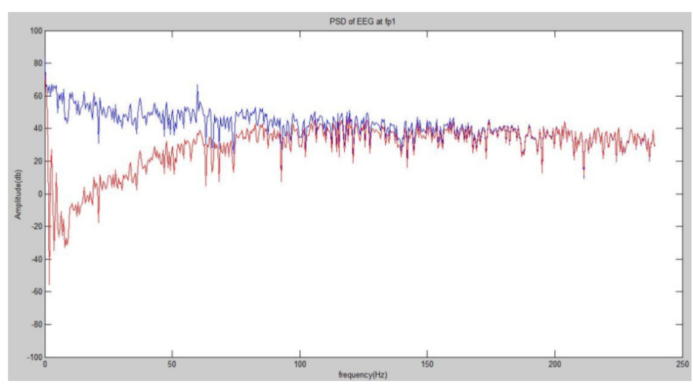

Fig. 8. PSD plot of output EEG signal given by Wavelet transform

IV. Conclusion

The performance of two methods such as JADE and wavelet transform were discussed in this paper. In case of JADE, in order to estimate the fourth order cross cumulants , a storage problem comes into picture. In case of wavelet transform, thresholding should be carefully done so that it does not remove the underlying EEG data components.Whether thresholding should be applied to entire signal or only artifacts or the detail coefficients should also be taken into consideration.The two methods used in this paper suppress most of the artifact portions. New techniques such as adaptive filter algorithms can be implemented.

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