Comparison of ICA-Based JADE and SOBI Methods EOG Artifacts Removal

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***Abstract*—Electroencephalogram (EEG) is the activity of bioelectrical signals that recorded from electrodes on the scalp. In EEG recording, the signal obtained is not entirely derived from the brain, but may be contaminated by other signals such as Electrooculogram (EOG), Electrocardiogram (ECG) and Electromiogram (EMG). EEG signals that recorded, especially by electrodes located near the eyes, will be affected by EOG. So that necessary action is needed to eliminate or reduce these EEG signals artifacts. This paper proposed a method using ICA for EOG artifact removal and compared which ICA algorithm (JADE and SOBI) is more effective and has better results in the removal of EOG artifacts in EEG recording.**

***Index Terms*—EEG, Artifacts, EOG, ICA, JADE, SOBI**

I. Introduction

The Electroencephalogram (EEG) is a biological signal that represents the electrical activity of the brain [1]-[3]. Eye-blinks and movement of the eyeballs produce electrical signals that are collectively known as Ocular Artifacts (OA). These are of the order of milli-volts and they contaminate the EEG signals which are of the order of micro-volts. The frequency range of EEG signal is 0 to 64 Hz and the OA occur within the range of 0 to 16 Hz [4], [5]. In addition to the medical applications, EEG is also applied to Brain Computer Interface (BCI) systems [6]-[13]. Within a few decades, variety of applications of BCI has been developed to improve the quality of human life, such as typing systems [10], mouse cursor controling [11], web browser controling [12], and wheelchair controling [13].

In EEG recording, the signal obtained is not entirely derived from brain, but may be contaminated by other signals such as Electrooculogram (EOG), Electrocardiogram (ECG) and Electromiogram (EMG). Ocular Artifacts (eye movement and blink), noise that comes from muscle, heart signal, generate many artifacts in EEG signals recording [4]. These artifacts can interfere with the application of the EEG signal. In this paper, we are focus on EOG artifacts which generated by eye movement or blinking. EOG artifact has a high amplitude and low frequency components (the effects of EOG usually appear in the low frequency band of the EEG spectrum). Therefore, the actions to eliminate or reduce these artifacts of were necessary performed. The conventional filter methods can be used to remove noise and other components with higher frequency. The main problem is that the ocular artifacts has spectral which overlap with EEG, that can not be removed using conventional filter [4].

A variety of methods have been proposed for correcting ocular artifacts and are reviewed in [14]-[21]. One common strategy is artifact rejection. The rejection of epochs contaminated with OA is very laborious and time consuming and often result in considerable loss in the amount of data available for analysis. Eye fixation method in which the subject is asked to close their eyes or fix it on a target is often unrealistic. Widely used methods for removing OAs are based on regression in time domain or frequency domain techniques. This paper analysed ICA method for EOG artifact removal and compared the effectivity of ICA algorithm (JADE and SOBI). So that the algorithms performance in the removal of EOG artifacts in EEG recording can be compared.

II. Data Acquisition

Seven healthy subjects (all male, with age between 20-22 years old) participate in this study, subjects are untrained personal. Subject were sat in the chair that make them relax and were asked to watch the monitor to see the stimulation. The experiments were performed in two session. In the first session, subject were asked to close his eyes and in the second session subjects were asked to blink his eyes. EEG data were collected from 14 channels at a sampling rate of 128 Hz using Epoch EMOTIV Neuroheadset. Data were analyzed using custom Matlab scripts built on the open source EEGLAB toolbox, and ICA algorithms are available in the ICALAB toolbox for Signal Processing v.3. Data were filtered between 0.5 Hz and 49 Hz using a IIR filter Chebyshev Type II. Six channels were used in signal processing, F7, F8, T7, T8, O1, and O2 which is related to visual activity. To know which algorithm is better for artefacts separation, Signal to Interference Ratio (SIR) is used to analysis the processed data.

III. Methods

The standard linear ICA model canbe expressed as:

$$x(t) = \boldsymbol{A}.s(t) \tag{1}$$

where x represents a multi channel signal mixture of mutually independent sources s. It is necessary that the

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number of signals (sensor observations) in x is not less than the number of sources in s. Mixing matrix **A** is the unknown value and the purpose of an independent component analysis is to find an estimate of its inverse matrix **W** such that:

$$y(t) = \boldsymbol{W}.x(t) \quad (2)$$

Signal y represents independent components that actually estimate sources s. There is a limitation of the ICA method which estimated signal y_i cannot determine the variance of a source s_i so that there is an infinite number of factors α_i:

$$y_i(t) = \frac{1}{\alpha_i}.s_i(t) \quad (3)$$

Fortunately, the value of the α_i can be choosen in a way that a unit variance is achieved [18].

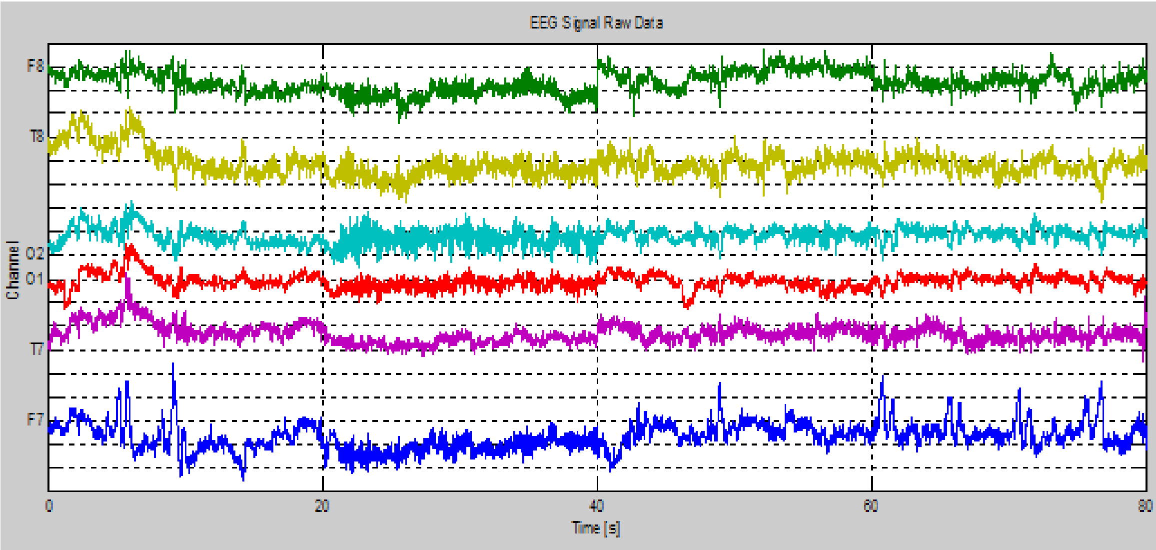


Figure 1. Raw data contaminated EOG artifacts.

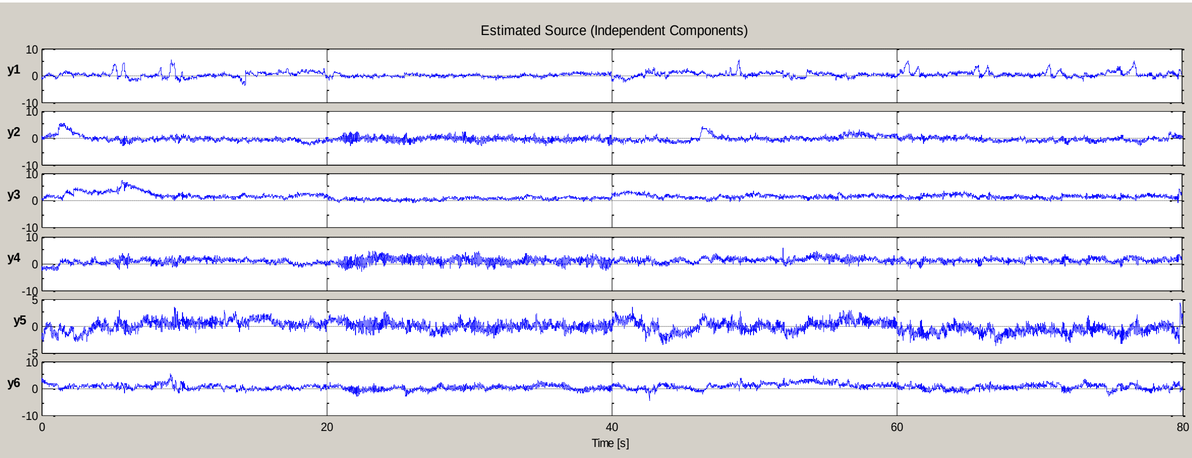


Figure 2. Estimated sources of EEG signals using JADE algorithm: (a) normal, (b) close ayes, (c) ayes blink.

In order to calculate the de–mixing matrix W, numerous ICA algorithms have been developed with various approaches. Two algorithms (SOBI and JADE) were used in artefact removal and comparition was made between those two algorithms. SOBI algorithm is very effective when independent sources are mutually uncorrelated, but correlated individually. It calculates second order statistics – covariance matrices, which are later diagonalized [21]. SOBI is defined by the following implementation: (i) Estimate the sample covariance $\widehat{\boldsymbol{R}}(0)$ from $\boldsymbol{T}$ data samples. Denote by $\lambda_i, \dots, \lambda_n$ the largest n eigenvalues and $h_i, \dots, h_n$ the corresponding eigenvectors of $\widehat{\boldsymbol{R}}(0)$. (ii) Under the white noise assumption, an estimate of $\hat{\sigma}^2$ the noise variance is the average of the $m-n$ smallest eigenvalues of $\widehat{\boldsymbol{R}}(0)$. The whitened signals are $z(t) = [z_1(t), \dots, z_n(t)]^T$, which are computed by $z_i(t) = (\lambda_i - \hat{\sigma}^2)^{-(1/2)} h_i^* x(t)$ for $1 \le i \le n$. This is equivalent to forming a whitening matrix by

$$\widehat{\boldsymbol{W}} = \left[(\lambda_1 - \hat{\sigma}^2)^{-(1/2)} h_1, \dots, (\lambda_n - \hat{\sigma}^2)^{-(1/2)} h_n \right]^H \quad (4)$$

(iii) Form sample estimates $\underline{\widehat{\boldsymbol{R}}}(\tau)$ by computing the sample covariance matrices of $z(t)$ for a fixed set of time lags $\tau \in \{\tau_j | j = 1, \dots, \boldsymbol{K}\}$. (iv) A unitary matrix $\widehat{\boldsymbol{U}}$ is then obtained as joint diagonalizer of the set $\{\underline{\widehat{\boldsymbol{R}}}(\tau_j) | j = 1, \dots, \boldsymbol{K}\}$. (v) The source signals are estimated as $\hat{s}(t) =$

$\widehat{\boldsymbol{U}}^H\widehat{\boldsymbol{W}}x(t)$, and/or the mixing matrix $\boldsymbol{A}$ is estimated as $\widehat{\boldsymbol{A}} = \widehat{W}^{\#}\widehat{U}$ [22].

JADE algorithm uses fourth order moments (cumulant matrices) to separate sources from the mixed signals. It employs joint approximate diagonalization to create cumulant matrices as diagonal as possible [21]. JADE can now be described by the following steps: (i) Form the sample covariance $\widehat{\boldsymbol{R}}(0)$ and compute a whitening matrix $\widehat{\boldsymbol{W}}$. (ii) Form the sample fourth-order cumulant of the whitened process $\hat{z}(t) = \widehat{\boldsymbol{W}}x(t)$; compute the n most significant eigenpairs $\{\hat{\lambda}_r, \widehat{\boldsymbol{M}}_r | 1 \le r \le n\}$. (iii) Jointly diagonalise the set $\widehat{N}^e\{\hat{\lambda}_r, \widehat{\boldsymbol{M}}_r | 1 \le r \le n\}$ by unitary matrix U. (iv) An estimate of $\boldsymbol{A}$ is $\widehat{\boldsymbol{A}} = \widehat{W}^{\#}\widehat{U}$ [23].

IV. RESULTS

The continuous data have been recorded and its signal was shown in Fig. 1. This data was filtered using Chebyshev Type II and then extracted using ICALAB with two different algorithm (JADE and SOBI). ICALAB can show various of analysis such as Sources, Estimated Sources (Independent Component), and SIR for mixing matrix A and Sources. Fig. 2 and Fig. 3 show the estimated sources using JADE and SOBI algorithm, respectively. By visually comparing the time domain plots, it is clear that the both proposed algorithm reduces the amplitude of the ocular artifact while preserving the background EEG.

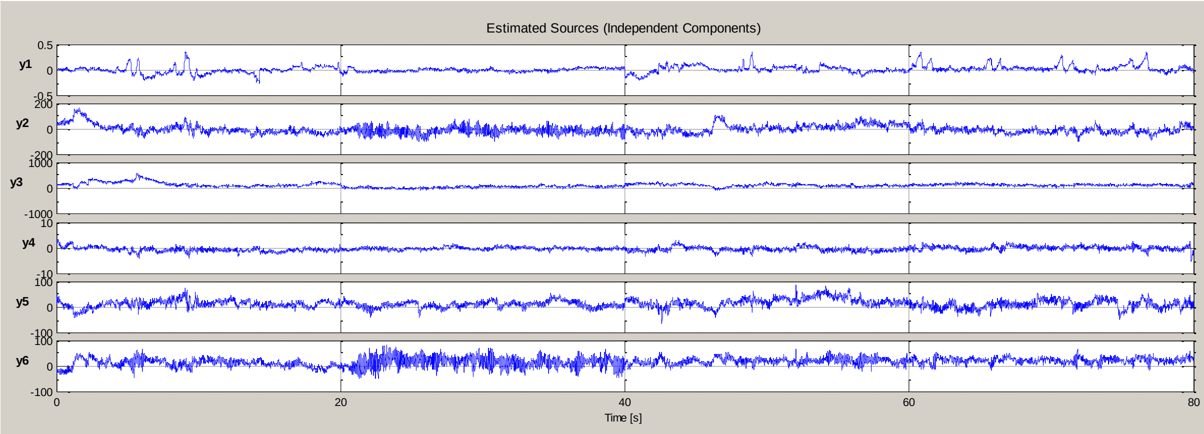
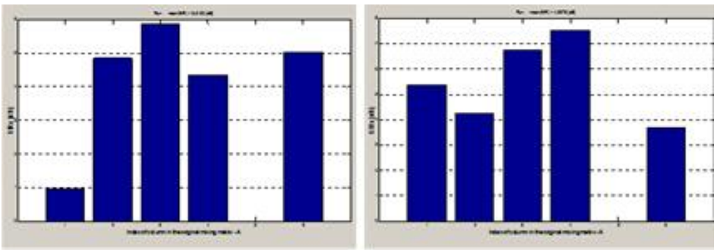
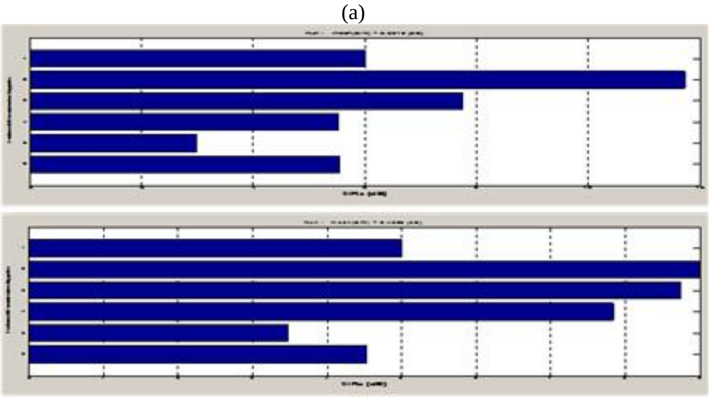


Figure 3. Estimated sources of EEG signals using JADE algorithm: (a) normal, (b) close ayes, (c) ayes blink



(a)



(b)

Figure 4. Signal to Interference Ratio (a) SIR A (b) SIR S.

In the generated demixing, the accuracy of an ICA algorithm cannot be described using only by the estimated mixing matrix. It is important to measure how well ICA algorithms estimate the sources, and the most commonly used index to assess the quality of algorithm is SIR as shown in Fig. 4. Higher value of SIR means that the algorithm performs better artefact separation. In Table 1, the SIR of each algorithm for each subjects and the mean of SIR from seven subjects are presented. JADE algorithm has a smaller value of SIR than SOBI, the mean of SIR A for JADE is 3,590 and SIR S is 5,393 whereas the mean of SIR A for SOBI is 4,083 and SIR S is 8,038.

TABLE I. SIR COMPARISON FOR TWO ICA ALGORITHM

NO.	METHODS	JADE			SOBI		
		SIR A		SIR S	SIR A		SIR S
	Subjects	Performance Index	Mean [dB]	Mean [dB]	Performance Index	Mean [dB]	Mean [dB]
1	Subject 1	0,310	3,515	6,592	0,238	4,598	6,431
2	Subject 2	0,244	4,869	6,170	0,293	3,642	8,743
3	Subject 3	0,360	2,612	4,812	0,241	6,397	9,891
4	Subject 4	0,266	4,022	4,919	0,355	2,693	6,745
5	Subject 5	0,289	3,226	6,091	0,262	4,494	7,313
6	Subject 6	0,431	1,175	3,987	0,308	2,965	8,668
7	Subject 7	0,209	5,709	5,182	0,302	3,793	8,476
Mean		0,301	3,590	5,393	0,286	4,083	8,038

V. CONCLUSIONS

This paper analysed the method, based on ICA algorithm for EOG artifacts removal. JADE and SOBI algorithm was used in this paper for comparison which one is better. SOBI has a higher value of SIR than JADE, which means that SOBI algorithm perform separation and removal of EOG artifacts better than JADE. SOBI is limited in separating out short-duration signals such as eye blinks. The proposed method minimizes the amplitude of the ocular artifact, while preserving the magnitude and phase of the high frequency background EEG activity.

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