EOG Artifacts Removal in EEG Measurements for Affective Interaction with Brain Computer Interface

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***Abstract*—A brain-computer interface (BCI) is a direct link between the brain and a computer. Multi-modal input with BCI forms a promising solution for creating rich gaming experience. Electroencephalography (EEG) measurement is the sole necessary component for a BCI system. EEG signals have the characteristics of large amount, multiple channels and sensitive to noise. The amount of valuable information derived from EEG signals is dependent on both the amount of noises embedded in the original measurement and the algorithms selected for postprocessing. Therefore, artifacts removal in the preprocess step is crucial. Electrooculography (EOG) signals are one of the major artifacts that often appear in EEG measurement. In this paper, we compared two different algorithms (Recursive Least Square (RLS) and Blind Source Separation (BSS)) to investigate their performances on removing EOG artifacts from EEG signals. Results indicate that the performance of RLS algorithm is better than BSS algorithm no matter whether there are any EOG reference signals. For BSS algorithm, the performance is better when EOG reference signals are available. These results show that for a BCI system, EEG reference is often necessary. Performance will be sacrificed if an EEG system cannot have any EOG reference signals.**

***Keywords*-Electroencephalography (EEG); Electrooculography (EOG); Blind Source Separation; Second Order-Blind Identification (SOBI); Recursive Least Square (RLS); Artifacts**

I. INTRODUCTION

In recent years, there has been growing interests in using BCI as a new form of interaction modality for gaming. BCI would not be just a substitute for classical interaction peripherals, such as joysticks, but rather a complementary means of interaction. One possible application to promote BCI usage is videogames. With BCI, the interaction protocol becomes invisible to the game player. Present BCIs use EEG activity recorded at the scalp to perfom interaction control. EEG signals have the characteristics of low aptitude, multiple channels and sensitive to noise. A complete chain of EEG signal processing will consist of preprocessing, feature extraction and feature classification. In order to derive valuable clinical or diagnostic information from EEG measurement, artifacts removal is necessary and crucial. The artifacts often founded in EEG measurement are EOG, Electromyography (EMG) and ECG signals. Possible body movement related motion artifacts are often seen as well. Since most of EEG measurements are performed in still conditions, motion artifacts can be avoidable. Because eye movement is unavoidable, EOG signals become one of the major artifacts that exist in EEG measurement. There are at least two types of EOG signals: horizontal EOG (HEOG) and vertical EOG (VEOG). They are produced by corresponding eye movements or eye blink, as illustrated in Figure 1.

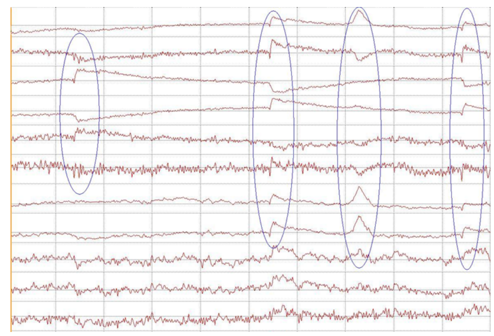

Figure 1. Typical EOG artifacts in EEG measurements

II. RELATED WORK IN EOG ARTIFACTS REMOVAL

Various algorithms exist in order to remove EOG artifacts embedded in the EEG measurements. These algorithms can be classified into several major groups: regression/adaptive filtering, spatial components or blind source separation (BSS). Regression-based methods were introduced by researchers in earlier works of artifacts removal due to its simplicity of the principle and low computational cost as well. Regression based methods can applied to either in time domain [1], [2] or frequency domain [3], [4], [5]. With these regression methods, EOG signals are required as references along with the EEG signals. The second method is based on Principal Component Analysis (PCA) [6], [7]. With PCA, EEG signals are transposed into several principal components using its eigenvector. Then particular components that contain EOG artifacts are removed. Those principal components without EOG components are converted back to the original data space. From statistics point of view, the decomposed signals by PCA are uncorrelated, but not necessarily independent. Independent Component Analysis (ICA) is another alternative approach. ICA can be regarded as an extension of PCA, but does not have the same constraint of orthogonality as PCA. ICA assumes the decomposed components as approximately independent rather than simply uncorrelated. Both these methods require great computations and need many numbers of recording channels in order to have reliable and accurate source estimation and artifact removal process [8], [9]. There are some other methods introduced by researchers, such as wavelet [10], and dipole modeling [11], [12]. They have not been the major interests for most of researchers in EOG artifacts removal. Overall, there is no consensus regarding which algorithm is superior to the others in terms of performance. Experimental evidences show different results due to the differences of measured signals in terms of electrode positions and channel numbers. Evaluation protocols are often defined differently.

III. Algorithm Selection and Data Collection

We have selected recursive least square (RLS) and second order blind identification (SOBI) algorithms in our study for EOG artifacts removal [13], [14], [15]. We chose these two algorithms because they are representative in term of algorithm simplicity and performance. For the first algorithm, it is necessary to have the EOG signals as reference due to the algorithm itself. However, the advantage of this algorithm is that computational cost is quite low. SOBI has been selected since it is a typical representative of spatial filter methods. Such methods do not need to have reference EOG signals. However, it is difficult to make the removal process automatically due to the intermediate step of component selection.

A. Recursive Least Square (RLS)

In general, the mathematical expression of EOG artifacts embedded in EEG measurement can be represented as follows:

$$EEG_{measured}(n) = EEG_{clean}(n) + NOISE(n) \quad (1)$$

Here, $EEG_{measured}$ represent the samples of EEG collected from a certain number of electrodes (n). $EEG_{clean}(n)$ are the desired/original clean EEG signals. $NOISE(n)$ represent the noises created by eye or/and muscle movement. In this paper, we simplify the noises embedded in EEG measurement are only EOG. EOG noise components will consist of horizontal and vertical eye movement.

$$EEG_{measured}(n) = EEG_{clean}(n) + EOG(n) \quad (2)$$

To drive clean EEG signals from measured signals with two finite impulse response (FIR) filters, the expression 2 can represented as

$$\begin{aligned} EEG_{clean} &\approx EEG_{corrected}(n) \\ &= EEG_{measured}(n) - \overline{EOG_h} - \overline{EOG_v} \end{aligned} \quad (3)$$

Where $\overline{EOG_h}$ and $\overline{EOG_v}$ represents the filtered reference EOG signals (horizontal and vertical). For FIR filters, $\overline{EOG_h}$ and $\overline{EOG_v}$ can be derived from two reference inputs EOG_h and EOG_v as the following equations describe:

$$\overline{EOG_h} = \sum_{m=1}^{M} h_h(m) EOG_h(n+1-m) \quad (4)$$

$$\overline{EOG_v} = \sum_{m=1}^{M} h_v(m) EOG_v(n+1-m) \quad (5)$$

$h_h(m)$ and $h_v(m)$ represent the nth coefficients of two FIR filters of length M.

The objective of removing EOG artifacts is to produce output signals $EEG_{corrected}(n)$ that are as close to $EEG_{clean}(n)$ as possible, by adjusting the filter coefficients $h_h(m)$ and $h_v(m)$. By minimizing $\overline{EOG_h}$ and $\overline{EOG_v}$ with the recursive least-square (RLS) algorithm, $EEG_{corrected}(n)$ can be obtained. More details about the algorithm can be found in He et al. [13].

B. Blind Source Separation (BSS)

Blind source separation (BSS) methods (for example SOBI) for EOG artifacts removal are built upon a linear mixture model of the EEG source $EEG_{source}(n)$ and the ocular activity $EOG_{source}(n)$.

$$\begin{aligned} \left[\begin{array}{c} EEG_{observed} \\ EOG_{observed} \end{array} \right] &= A \times \left[\begin{array}{c} EEG_{source} \\ EOG_{source} \end{array} \right] \\ &= \left[\begin{array}{cc} a_{N\times N} & b_{M\times N} \\ c_{N\times M} & d_{M\times M} \end{array} \right] \times \left[\begin{array}{c} EEG_{source} \\ EOG_{source} \end{array} \right] \end{aligned} \quad (6)$$

Where A is the mixing matrix, EEG_{source} and EOG_{source} are the observed EEG and EOG channels respectively. The inverse of the mixing matrix is called the unmixing matrix W

$$W = A^{-1} = \left[\begin{array}{cc} U_{N\times N} & V_{M\times N} \\ Y_{N\times M} & X_{M\times M} \end{array} \right] \quad (7)$$

Which is used for reconstructing the and components from the observed data Among BSS methods, SOBI is able to estimate matrix A as long as the unknown source signals are temporally uncorrelated to each other but having non-zero time-delayed autocorrelations [14]. This is a plausible assumption for the case of EEG and EOG sources. SOBI computes the mixing matrix as the matrix that jointly diagonalizes a set of p cross-correlation matrices

$$R(\tau_i) = E[EEG_{observed}(t) EEG_{observed}(t-\tau_i)] \quad (8)$$

where i = 1.,...,p, and E[ ] is the expectation operator. With SOBI, n-channel continuous EEG signals can be decomposed into the same number of SOBI components, which corresponds to those recovered putative sources that

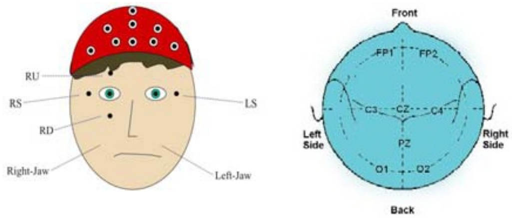

Figure 2. Electrodes positions of EOG and EEG

contribute to the scalp EEG signals. Every individual SOBI-decomposed putative component has a time course of activitation and an associated sensor space projection that specifies the effect of that putative source on each of the n electrodes.

C. Data Collection

In order to compare the algorithm performances, we collect both EEG and EOG measurements through our controlled experiments with particular protocol.

1) Experimental Collection: Ten healthy subjects (10 male, age between 20 and 31) took part in the experiments. Eight EEG channels, four monopolar EOG channels, two EMG channels (see Figure 2) were recorded with ECI Electro-Cap Electrode System and pre-gelled Ag/AgCl electrodes. They shared a common reference electrode at the left mastoid and a ground electrode at the right mastoid. In this study, only the EEG and EOG channels were used. These eight EEG channels were chosen as examples of frontal, parental and occipital lateral sites and as the centurial site, of the scalp, which are clinically important and relevant to our target applications. Two of the four EOG electrodes were positioned above and below the right eye. Another two electrodes are put on the outer canthi of the eyes. The bipolar EOG channels left-right and up-down were able to capture horizontal and the vertical/radial EOG components. Two EMG electrodes were positioned on the left and right side of the cheek for every participant.

The acquired EEG and EOG data was band pass filtered with a broadband anti-aliasing filter from 0.1 to 60 Hz and a 50 Hz notch filter, sampled with 256 Hz and 12 bit quantization. The dynamic ranges for EEG and EOG signals were 100 μ V and 1 mV, respectively. The recording system consisted of one 16-channel amplifier (g.tec USBMP, Graz, Austria), and a commercial desktop PC with two VGA output running under Windows XP. The software for data recording is G-recorder that was provided with g.tec. The software for creating animation to guide eye movement and controlling the experiment was implemented in MATLAB R2010a (The MathWorks, Inc., Natick, USA).

During the experiment, participants were asked to sit in front of a LCD monitor and instructed not to move and keep still. Each subject was asked to perform 5 steps of actions for eye movement and 2 steps of actions for facial muscle movement. Details can be found in Table I.

Table I
EYE AND FACIAL MUSCLE MOVEMENT PROTOCOL

Movement	Actions
Eye	- Step1 eye close and closing (1 minute) - Step2 left and right movement (5 times) - Step3 up and down movement (5 times) - Step4 blink (5 times) - Step5 natural eye movement of text reading (1 minute)
Facial muscle	- Step1 mouth opening and closing - Step2 gum chewing (half minute)

2) Simulation data: The nature of EEG measurement leads to the fact that it is difficult to retrieve artifact-free EEG data. In order to use SNR (signal noise- ratio) to evaluate algorithm performance, simulation data were reconstructed from the collected data. The EEG measurements of channel O1 and O2 are selected as clean EEG signals. EOG signals (left-right movement, up-down movement, and blink) were added into these clean signals to create contaminated EEG signals. As the scaling factors, α and β is used to create different SNRs.

$$EEG_{contaminated-s} = EEG_{clean} + \alpha \times EOG_v + \beta \times EOG_h \tag{9}$$

IV. RESULTS

With aforementioned data, the selected algorithms including BSS and RLS were applied to the simulation data. For the BSS algorithm, there are two types of configurations: with (w/EOG) and without EOG reference signals (w/o EOG). In this way, we investigate the relative performance of each algorithm for each type of EOG artifact (left-right movement, blink, and updown movement). Deferent evaluation metrics has been applied by researchers during investigating the algorithm performance for artifacts removal. There is no consensus on which metrics is superior to the others partly because clean EEG signals do not exist and cannot measure directly and easily. In this paper, the metrics we use include correlation both in frequency and time domain, root mean square (RMS) of difference between clean and corrected signals

A. Visual Comparison

To measure the effects of EOG artifacts removal, one direct approach will be the visual inspection of the signals. Figure 3 show the corrected EEG signals after applying these three methods. The original EOG and contaminated EEG signals with eye blink artifact are also shown in Figure 3.

B. Power Spectral Density

EOG artifacts, for example, eye blink often show unique frequency response. It is mainly reflected in low frequency range from 0.1 - 5 Hz. By looking at the power spectral

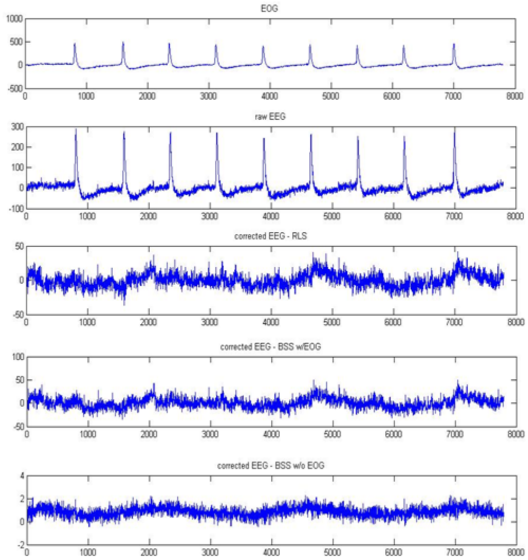

Figure 3. Corrected EEG signals created by three methods. Raw EEG signals with blink artifact and EOG signals are included

density, we can investigate the performance of all these algorithms in frequency domain (see Figure 4).

Table II
RESULTS OF THREE ALGORITHMS FOR EYE BLINK ARTIFACTS

	RLS	BSS w/ EOG	BSS w/o EOG
Correlation in time domain	0.9801	0.995	0.3594
Correlation in frequency domain	0.9999	0.9999	0.983

C. Correlation in time and frequency domain

The performances of these three methods are further compared using the correlation coefficient between clean EEG signals and corrected EEG signals in time and frequency domain. Results are summarized in Table II. After applying the BSS method with EOG reference signal, the corrected EEG signal has the highest correlation in time and frequency domain with the clean EEG signal.

D. Average Results

In this section, the performances of three methods applied to all ten subjects are summarized. Correlations coefficient in time and frequency domain are calculated with different SNRs as input. RMS of differences between clean and corrected EEG signals is also calculated.

Figure 5 shows the correlation coefficient in frequency domain between the correct and clean EEG signals. Results indicate that RLS method has the highest correlation and the correlation increases as SNR increases. On the contrary, for the other two methods, as SNR increases, the correlations decrease. The performance of BSS method without EOG reference signal is the lowest.

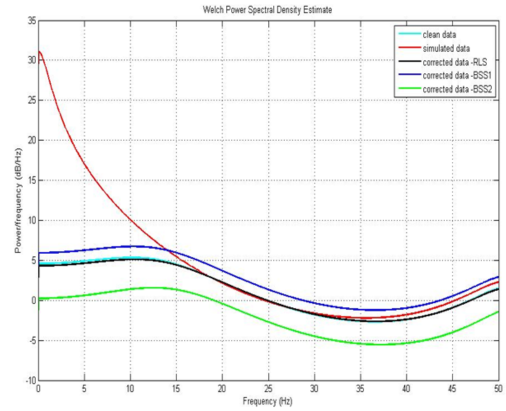

Figure 4. Power spectral density for clean EEG, simulation EEG, and corrected EEG data

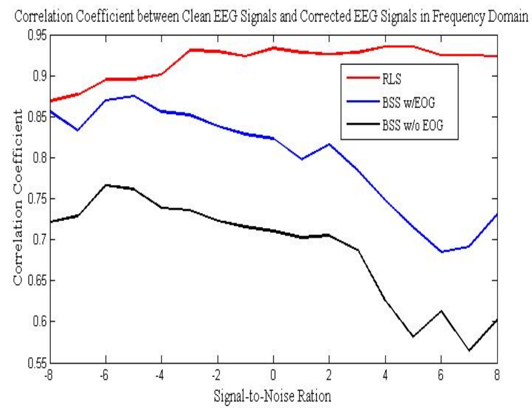

Figure 5. Correlation coefficient for left_right eye movement

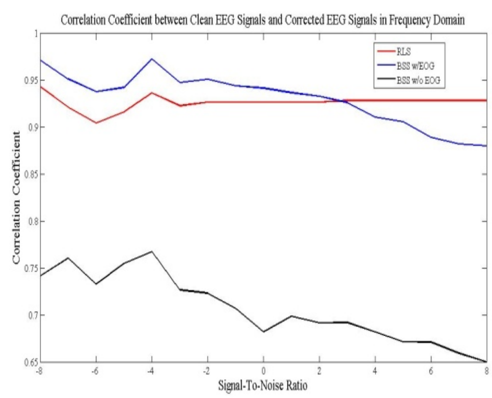

Figure 6. Correlation coefficient for up_down eye movement

Figure 6 shows the correlation coefficient in frequency domain between the corrected and clean EEG signals for the up-down eye movement artifact after applying the three

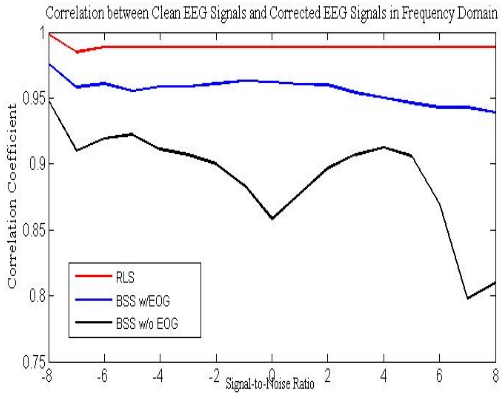

Figure 7. Correlation coefficient for eye blink artifacts

methods to contaminated EEG signal. Surprisingly the BSS method with EOG reference leads to the highest correlation coefficient and only till SNR increases up to 3 and higher, the correlation coefficient for the RLS method becomes the highest.

Figure 7 shows the correlation coefficient in frequency domain between corrected and clean EEG signals after applying the three methods to contaminated EEG signal with eye blink movement artifact. Still RLS method leads to the highest correlation in frequency domain but the differences among all three methods are not that big. For RLS method, the correlation coefficient does not change much as the SNR increases.

V. Conclusion

In this paper, we compared the performance of two major algorithms (BSS and RLS) with three configurations for removing three kinds of EOG artifacts in EEG measurements. For BSS algorithm, we investigated the effects of with and without EOG reference signals. A simulation database is constructed through a controlled experiment and used to benchmarking the algorithms. RLS method has shown the best performance most of time in frequency domain. While there is no EOG reference signal, the performance of BSS method decreases. Future work will include measuring the algorithm performance with real EEG measurement and optimizing the algorithm for real time environment.

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