The Removal Of Ocular Artifacts From EEG Signals: A Comparison of Performances For Different Methods

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Abstract — **The presence of electrooculographic (EOG) artifacts in the electroencephalographic (EEG) signal is a major problem in the study of brain potentials. A variety of algorithms have been proposed to reject these artifacts including methods based on regression and blind source separation (BSS) techniques. None of them has so far been established as the method of choice. In the present study, the performances of five widely used EOG artifact rejection techniques are compared. The compared methodologies include two fully automated regression methods, one based on Least Mean Square (LMS) for its optimization process, and the other on Recursive Least Square (RLS) algorithm, two BSS techniques which use respectively the Extended – Independent Component Analysis (ext – ICA) and the Second Order Blind Identification (SOBI), and finally a time–varying adaptive algorithm based on H^{∞} principles ($H^{\infty}-TV$). Each algorithm was applied in real EEG data and then their performance quantified in the time domain. The performance of RLS and $H^{\infty}-TV$ were poor in removing eye – blink artifacts. For the rest of the methods the results supported the use of LMS technique and suggested the need for further research examining the performance of various artifact rejection techniques in both time and frequency domain.**

Keywords — **EOG, EEG, Artifacts, LMS, ICA**

I. Introduction

Artifacts are the outstanding enemies of high quality EEG signals. Their presence is thus crucial for the accurate evaluation of EEG signal. They fall into two major categories: technical and physiological artifacts. The most frequently seen physiological artifacts are due to ocular, heart or muscular activity; among them the EOG artifacts are the most troublesome.

It is known that cornea is positively charged in reference to retina. This retino – corneal potential difference generates a dipole within the eyeball, which is responsible for the EEG signal distortion while the eye moves. The eye–blinking artifact could also be the result of alternations in conductance arising from the contact of eyelid with the cornea [1].

The Event–Related Potentials (ERP) can be seriously affected by ocular artifacts. A classical approach to prevent these artifacts is by restricting eye movements or by rejecting the contaminated trials. The restriction of eye movements may oppress the subject harming the cerebral cognitive processes. On the other hand the removal of contaminated trials may lead to unacceptable data loss.

Computer-based systems have been proposed for the detection and correction of EOG artifacts. These systems make use of different artifact rejection techniques. There are two main approaches: the regression methods, and the BSS methods. The regression methods compute the backward propagation coefficients in order to define the amplitude relation between the EEG and EOG channels and subtract the EOGs from the EEGs signals [2]. The performance of regression analysis can be severely affected by the bidirectional contamination; since ocular activity can contaminate EEG signals, then cerebral activity can also contaminate the EOG recordings. To overcome this problem, it has been suggested [3] that before applying regression methodology, the EOG signals should be low–pass filtered removing both cerebral and ocular high frequencies.

BSS techniques have the ability to separate EEG signals to spatial components; specialists are then called to identify the artifactual components remove them and reconstruct the signal so as to be free of artifacts. The main disadvantage of this methodology is that specialists should be available to recognize and reject the artifactual components. This is a time consuming procedure which can lead to cerebral activity distortions if will not be performed with great care [4].

Limited literature ([5], [6], [7]) is available testing and comparing the performance of different artifact rejection techniques to remove EOG artifacts from the EEG signal. Here, the performance of five different algorithms was assessed in detecting and rejecting EOG artifacts. The compared methods include two adaptive filtering regression techniques [8], [9], two BSS approaches [10], [4] and one adaptive noise cancellation (ANC) scheme [11].

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II. Material and methods

Sixteen healthy subjects (8 males and 8 females) participated in an emotion evocative-stimuli experiment. The subjects were passively observing four blocks of emotional pictures consisted of 120 trials, selected from International Affective Picture System (IAPS) [12] presented on a PC monitor.

During the experiment, multichannel EEG and EOG measurements were performed. Nineteen EEG electrodes were placed according to the 10-20 International System. Two EOG electrodes were placed above and below the left eye and another two on the outer canthi of each eye. Two bipolar signals were obtained from these four EOG electrodes, namely vertical-EOG (VEOG), which is equal to upper minus lower electrode values and horizontal-EOG (HEOG), which is equal to left minus right electrode values.

A band-pass filter (0.5-40 Hz) and a notch filter at 50 Hz for line noise extraction were applied to the raw EEG signals. EOG signals were also notch filtered at 50 Hz and band-passed filtered in the frequency band of 0.5-13 Hz so as high frequencies derived from cerebral and ocular activity to be removed [3].

The observers identified totally 1968 eye blinks on 64 datasets. Each artifact rejection technique was applied to the whole signal of all datasets. All algorithms are available in the Automatic Artifact Rejection plugin (ver.1.3) of EEGLAB [13] (http://sccn.ucsd.edu/eeglab/plugins.html) except Ext-ICA. To assess the performance of each algorithm, one hundred trials contaminated by eye-blinks were randomly selected from the aforementioned datasets. The performance of each algorithm was estimated for each of the above trials using the following formula:

$$Per = \max(C_{EEG,EOG}(d)) - \max(C_{CEEG,EOG}(d)) \qquad (1)$$

where $C_{EEG,EOG}(d)$ denoting the cross-correlation sequence between the contaminated EEG and EOG signals and $C_{CEEG,EOG}(d)$ denoting the cross-correlation sequence between the artifact-free EEG and EOG signals.

One-way ANOVA was then applied in the Performance values to examine possible statistical significance differences between the algorithm's efficiency.

A. Adaptive Filters – Regression Techniques

Most of linear adaptive filtering problems can be formulated as depicted in the following block diagram in Fig.1

Their goal is to adjust the filter coefficients $\hat{w}(n)$ and make them approach the optimal filter coefficients $w(n)$ as

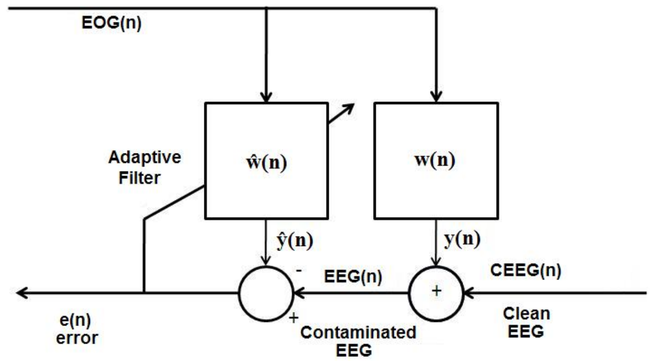

Fig.1 $EEG(n) = w(n)EOG(n) + CEEG(n)$. Adaption filtering is trying to adjust $\hat{w}(n)$ as close as possible to $w(n)$, so our goal is to approach clean EEG as much as possible $e(n) = EEG(n) - \hat{w}(n)EOG(n)$.

close as possible, so that the quantity $EEG(n)$ tends to be equal to $CEEG(n)$. From a mathematical point of view, this requires the minimization of the following objective function,

$$F(n) = E\left\{ |e(n)|^2 \right\} \qquad (2)$$

where $e(n)$ is the error from the above block diagram and $E\{\ldots\}$ denotes the expected value. For this purpose, LMS, RLS and $H^{\infty} - TV$ algorithms are employed. The implementation summary of LMS, RLS and $H^{\infty} - TV$ are illustrated in Table 1, Table 2 and Table 3 respectively.

Table 1 Description of the LMS Algorithm

Input: Contaminated EEG and two EOG channel as a reference (VEOG, HEOG)

Output: Clean EEG.

Parameters:

p = the order of adaptive filter (here $p = 3$)

μ = step size (here $\mu = 10^{-6}$)

Initialization: $\hat{w}(0) = 0$

Computation: for $n = 1,2,\ldots$

$EOG(n) = [EOG(n), EOG(n-1), \ldots EOG(n-p+1)]^T$

$e(n) = EEG(n) - \hat{w}^H(n)EOG(n)$

$\hat{w}(n+1) = \hat{w}(n) + \mu EOG(n)e(n)$

where $\hat{w}^H$ is the conjugate transpose of $\hat{w}$.

Table 2 Description of the RLS Algorithm

Input: Contaminated EEG and two EOG channels as reference (VEOG,HEOG)
Output: Clean EEG.

Parameters:
$p =$ the order of adaptive filter (here $p = 3$)
$\lambda =$ forgetting factor (here $\lambda = 0.9999$)
$\sigma =$ value to initialize $P(0)$ (here $\sigma = 0.01$)

Initialization: $\hat{w}(0) = 0$, $P(0) = I/\sigma$, where I is the $(p+1)\times(p+1)$ identity matrix

Computation: for $n = 1,2,\ldots$

$$EOG(n) = [EOG(n), EOG(n-1), \ldots EOG(n-p)]^T$$

$$a(n) = EEG(n) - \hat{w}^T(n-1)EOG(n)$$

$$g(n) = \frac{P(n-1)EOG^*(n)}{\lambda + EOG^T(n)P(n-1)EOG^*(n)}$$

$$P(n) = \lambda^{-1}P(n-1) - g(n)EOG^T(n)\lambda^{-1}P(n-1)$$

$$\hat{w}(n) = \hat{w}(n-1) + a(n)g(n)$$

$$e(n) = EEG(n) - \hat{w}^T(n)EOG(n)$$

Table 3 Description of $H^\infty - TV$ Algorithm

Input: Contaminated EEG and two EOG channels as reference (VEOG,HEOG)
Output: Clean EEG.
Parameters:
$p =$ the order of adaptive filter (here $p = 3$)
$\eta =$ the distance at $t = 0$ to optimal solution (here $\eta = 0.005$)
$\rho =$ speed of variation of filter coefficients (here $\rho = 10^{-5}$)
$\varepsilon =$ positive constant variant (here $\varepsilon = 1.5$)

Initialization:
$\hat{w}(0) = 0$, $\Pi_0 = \eta I$, $\Upsilon_0 = \rho I$, $P(0) = \eta I = \Pi_0$

Computation: for $n = 1,2,\ldots$

$$EOG(n) = [EOG(n), EOG(n-1), \ldots EOG(n-p+1)]^T$$

$$a(n) = EEG(n) - \hat{w}^T(n-1)EOG(n)$$

$$g(n) = \frac{\widetilde{P}(n)EOG^*(n)}{1 + EOG^T(n)\widetilde{P}(n-1)EOG^*(n)}$$

$$\widetilde{P}^{-1}(n) = P^{-1}(n) - \varepsilon^{-2}EOG(n)EOG^T(n)$$

$$P(n+1) = [P^{-1}(n) + (1-\varepsilon^{-2})EOG(n)EOG^T(n)]^{-1} + \Upsilon_0$$

$$\hat{w}(n+1) = \hat{w}(n) + a(n)g(n)$$

$$e(n) = EEG(n) - \hat{w}^T(n)EOG(n)$$

B. BSS Techniques

EEG signals (x_i) are a linear combination of several underlying brain sources (s_i). BSS techniques have the ability of finding a closest approach to the sources without a priori knowledge of them or the mixing process. Bell and Sejnowski [14] proposed a neural network algorithm for BSS which takes as input n EEG signals and extracts them to n statistical independent sources, using information maximization (infomax). Ext-ICA extends the ability of the infomax algorithm to perform BSS on recorded signals having either sub–Gaussian or super–Gaussian distributions [15].

In the present study Ext-ICA was applied to the 19 EEG signals giving 19 independent components (IC). Two independent observers identified the artifactual components using both the information from the raw potential waveforms and the scalp topographies. The artifactual components were visually removed and the signals were reconstructed without them.

The last algorithm used for our study is a recently proposed algorithm that makes use of SOBI algorithm for source extraction. In contrast to Ext-ICA where the identification of artifactual components is performed manually by the observers, this algorithm makes automatic identification and removal of artifactual components using Fractal Dimension (FD).

III. Results

RLS and $H^\infty - TV$ were unsuccessful in removing eye – blink artifacts from the EEG. In most trials, they fail to remove successfully the eye-blink artifact's amplitude (see Fig.2-RLS (purple), $H^\infty - TV$ (black)).

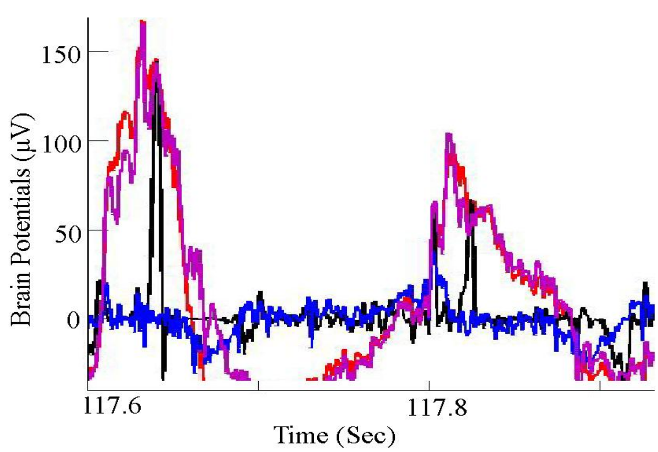

Fig.2 Plot of contaminated EEG (red), cleaned EEG with RLS (purple), cleaned EEG with $H^\infty - TV$ (black) and cleaned EEG with LMS (blue).

In contrast to RLS and $H^{\infty} - TV$, the rest methods removed completely the eye-blink artifacts from selected single trials. One-way ANOVA revealed statistically significant differences between their performances ($F(2,297)=3.291$, $p=0.039$). The LMS algorithm presented the best performance (0.23±0.11) in contrast to the other two algorithms that presented a performance of 0.2±0.11 (Ext-ICA) and 0.19±0.11 (FD) respectively (Fig.3).

In terms of computation cost, the LMS algorithm was faster than the other two procedures. LMS was performed in 5.98 sec, FD in 10.55 sec while Ext-ICA needed 243.39 sec only for the source extraction. The computation times were computed by using an AMD processor (Turion^{64}x2 2.00GHz, 2 GB RAM)

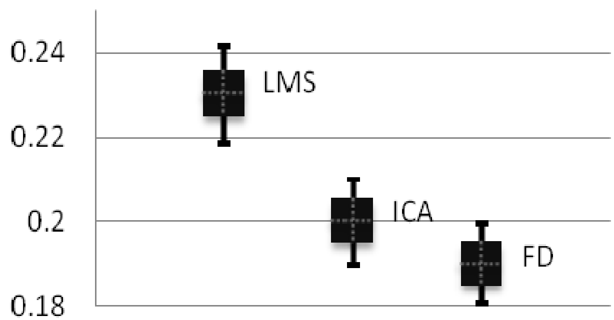

Fig.3 Mean values of each algorithm's performance with their standard deviation according to equation (1).

IV. Discussion

The LMS algorithm seems to successfully remove the eye-blink artifacts from the EEG signal presenting the best performance in comparison with the other two BSS algorithms. Its computation cost is also better. The technique of low-pass filtering the EOG signals before applying the LMS algorithm resulted to less cerebral activity subtraction from the EEG signal. It is however still unclear if the extracted artifactual components from BSS techniques, contain brain activity derived from the frontal lobe. Thus, the artifactual components removal will probably lead to unacceptably high distortions of EEG signal. As things stands now, no one can be confident if his/her method of choice distorts the recorded brain signal in the least possible way. Further research is necessary analyzing the signals in both time and frequency domain for this purpose.

V. Conclusions

The current study results suggest that the LMS algorithm removes the eye-blinks artifacts from the EEG signal more successfully and in less time than the other studied artifact rejection techniques.

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