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Intelligent ocular artifacts removal in a non-invasive single channel EEG recording

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Abstract— Muscle noises, line noises and eye movements are the main interferences that make difficulties when interpreting and analyzing electroencephalographic signals. Many methods have been proposed for artifacts removing from EEG measurements, and especially those arising from an ocular source. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) have been proposed to remove ocular artifacts from multichannel EEG. In contrast to this, we present a new algorithm for ocular artifacts removal from a single electroencephalographic channel recording. This method is based on a set of information on brain wave frequencies. Our results on EEG data, collected from healthy subjects, show that our algorithm can effectively detect and remove ocular artifacts in EEG recordings.

Keywords—ocular artifact; eeg; eog; brain signal; brain waves; brain signal frequencies

I. INTRODUCTION

Electroencephalography (EEG) is one of the most widely used brain exploration techniques to measure and analyze brain electrical activity. However, these measurements are usually contaminated by external electrical signals to the brain. Such interference can make difficulties when interpreting signals.

Electrical potentials generated during saccades and blinks can be of an order of magnitude greater than the electroencephalogram (EEG). These potentials can spread over a large part of the scalp and deform the EEG signals. In fact, a blink is characterized by a change in conductance due to the eyelid's movement on the cornea. This generates a visible transitory signal mainly in frontal and parietal electrodes. This signal is characterized by maximum amplitude and it can reach ten times the EEG signal amplitude.

Several studies based on independent component analysis [3,8] have been established to remove ocular artifacts from EEG signals. They have demonstrated their robustness and efficiency. In our study we propose a new method to detect and remove blinks. Given the emergent number of embedded systems in relation to the field of brain computer interfaces (BCI) for control [7], which converge remarkably towards the use of a very small number of electrodes, we decided to work on a single EEG channel.

This paper is organized as follows. Section II describes the main methods implemented in the ocular artifacts treatment context. Section III presents the implementation of our method. Experiments and results are described in section IV.

II. STATE OF THE ART

A. Electro-Oculogram (EOG) detection

We present in a first time an ocular artifacts filtering approach proposed by Gouy-Pailler[5]. This method was firstly developed by Dr. Reza Sameni[9,10] for filtering and extracting fetal cardiac signals. In this approach an electro-encephalogram (EOG) is used as a reference signal.

Let $\varphi(t)$ be the EOG channel, we define $\Phi(t)$ as the variance of the signal $\varphi(t)$ for a time interval defined by an ω window around t :

$$\Phi(t) = \frac{1}{\omega} \sum_{\tau=-\frac{\omega}{2}}^{\frac{\omega}{2}} \varphi(t - \tau)^2 \quad (1)$$

The ocular activity detection amounts to determine a threshold ℓ that will distinguish between the two following hypotheses:

- \mathcal{H}_0 : $\Phi(t) < \ell \Rightarrow$ no activity is detected .
- \mathcal{H}_1 : $\Phi(t) > \ell \Rightarrow$ period of ocular activity.

Let $\Phi_{\mathcal{H}_0}$ be the variance of $\varphi_{\mathcal{H}_0}(t)$ (the signal $\varphi(t)$ in \mathcal{H}_0 hypothesis), we assume that $\varphi_{\mathcal{H}_0}(t) \sim \mathcal{N}(0, \sigma_{\varphi_0}^2)$, then we can estimate the φ law variance $\sigma_{\varphi_0}^2$. However, assuming independence of $\varphi(t)$, we have:

$$\sum_{\frac{\omega}{2}}^{\frac{\omega}{2}} \frac{\varphi_{\mathcal{H}_0}(t)^2}{\sigma_{\varphi_0}^2} \sim \mathcal{G}\left(\frac{\omega}{2}, 2\right) \quad (2)$$

According to Gamma law:

$$\Phi_{\mathcal{H}_0}(t) \sim \mathcal{G}\left(\frac{\omega}{2}, \frac{2\sigma_{\varphi_0}^2}{\omega}\right) \quad (3)$$

This law allows setting the threshold so as to control the error by using the probability of false detections, (i.e. the probability of deciding \mathcal{H}_1 while \mathcal{H}_0 is true):

$$\begin{aligned} \mathbb{P}(\mathcal{H}_1|\mathcal{H}_0) &= \int_{\ell}^{\infty} x^{\frac{\omega}{2}-1} \cdot \frac{e^{-\frac{x\omega}{2\sigma_{\varphi_0}^2}}}{\frac{2\sigma_{\varphi_0}^2}{\omega} \Gamma\left(\frac{\omega}{2}\right)} dx \\ &= 1 - \int_{-\infty}^{\ell} x^{\frac{\omega}{2}-1} \cdot \frac{e^{-\frac{x\omega}{2\sigma_{\varphi_0}^2}}}{\frac{2\sigma_{\varphi_0}^2}{\omega} \Gamma\left(\frac{\omega}{2}\right)} dx \end{aligned} \quad (4)$$

where Γ is Gamma function.

Finally, using a numerical method for approximating the integral, the threshold ℓ can be calculated.

Once detecting the ocular activity, we attempt to perform a linear transformation W of the EEG signals $X(t)$ so that the result of this transformation is as similar as possible to the EOG:

$$Y(t) = W^T X(t) \quad (5)$$

B. Blind Sources Separation (BSS)

The aim of blind source separation (BSS) [1,2] is to recover the original sources given only sensor observations. In this approach, we assume that the source signals arrive simultaneously on the sensors. Noise mixture in this case is written as follows:

$$X = AS + N \quad (6)$$

where:

- X : mixed signals matrix.
- A : mixing matrix.
- S : independent source matrix.
- N : an additive noise matrix.

The aim of the BSS is to find a linear transformation T of signals X that makes them as independent as possible outputs:

$$Y = TX = TAS + TN \quad (7)$$

where:

Y is the estimation of S sources (assuming that the number of N_S sources is equal to the number of sensors N_C).

BSS algorithms seek the matrix T so that the TA product is a reduced and a diagonal matrix. Therefore the original source may be recovered except their order and amplitude. Estimated sources Y will be permuted and normalized to the standard deviation.

In simulated signals, we can validate the results of BSS using separability index (SI). This index is calculated from $G = TA$ transformation matrix between the original sources and the estimated sources.

The SI is calculated from the absolute values of the elements of G . The g_i line and g_j column of the matrix G are normalized for g'_i and g'_j respectively:

$$g'_i = \frac{|g_i|}{\max |g_i|}, \quad g'_j = \frac{|g_j|}{\max |g_j|} \quad (8)$$

We obtain IS_1 and IS_2 indexes from the resulting matrix $G' \in \mathbb{R}^{N_S \times N_S}$:

$$IS_1 = \frac{\sum_{i=1}^{N_S} (\sum_{j=1}^{N_S} (G'(i,j)) - 1)}{N_S \times (N_S - 1)} \quad (9)$$

$$IS_2 = \frac{\sum_{j=1}^{N_S} (\sum_{i=1}^{N_S} (G'(i,j)) - 1)}{N_S \times (N_S - 1)} \quad (10)$$

$$IS = \frac{IS_1 + IS_2}{2} \quad (11)$$

The purpose of the calculation of the SI index is to measure the degree to which G is close to a permutation matrix. For a perfect sources recovery, $SI = 0$.

III. ADOPTED MODEL

Ocular artifacts seen as a noise which distorts the EEG signal (Figure 1), and which may be due to saccades (very rapid eye movements, around 1000°/s) or due to blinks, which are characterized by very large amplitudes (x10 greater than EEG amplitude) (**Figure.1**).

The detection procedure proposed is based on the graphical representation of the EEG data distribution, for each subject, as a histogram. In almost all cases, the histogram was a Gaussian cloche (**Figure.2**), which allowed us to assume that the EEG signal follows a Normal Gaussian distribution:

$$X(t) \sim \mathcal{N}(\mu_X, \sigma_X^2) \quad (12)$$

where:

- $X(t)$: recorded signal.
- μ_X : EEG signal mean.

– σ_X^2 : EEG signal variance.

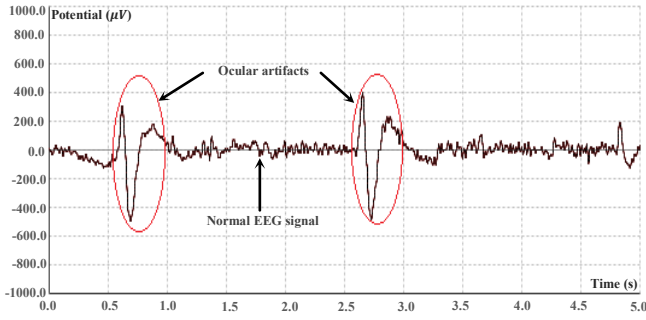


Figure.1 : Example of an ocular artifacts in EEG signal.

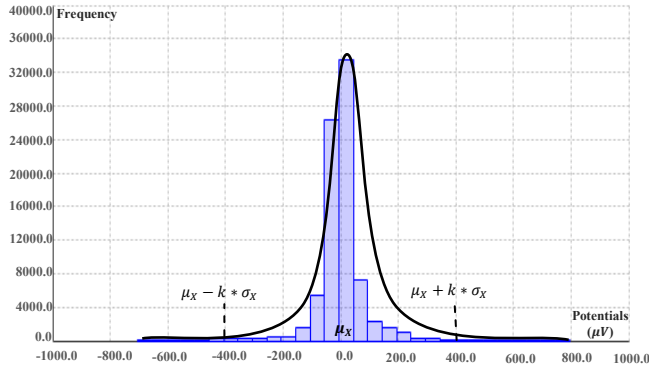


Figure.2 : Histogram example

This hypothesis has given us an idea about the way in which we could identify times of ocular artifacts. Indeed, in a Gaussian curve, the dominant values, which represent values of the EEG, are concentrated around the mean μ_X . There are values, which represent the large amplitudes, are distributed in the ends. These values can correspond to ocular artifacts. On the other hand, the interval $I = [\mu_X - k * \sigma_X, \mu_X + k * \sigma_X]$ ($k \in \mathbb{N}$ and σ_X is the standard deviation), contains a certain percentage of values. In practice, about 65% of the values belong to the interval I for $k = 2$. In our application, we have chosen to vary (from $k = 1$ to $k = 5$) the parameter k in different cases processed EEG data series. The interval I allows to set the bounds from which we can know whether a given value is an artifact or not (Figure.3).

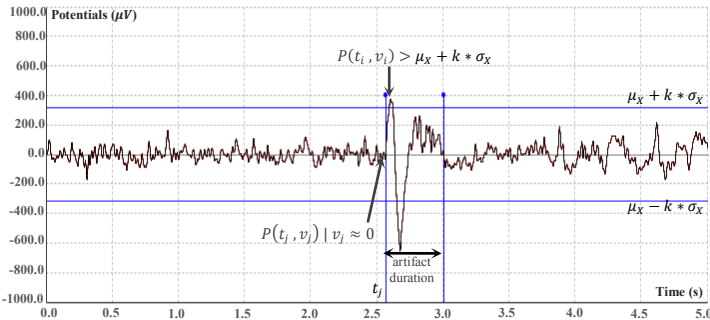


Figure.3: Detection of ocular artifacts instants.

Oncetheocular artifacts instants are determined, we proceed to their elimination from the EEG signal vector (Figure.5).

Algorithm *Blinks detection & elimination*

Require : $X \in \mathbb{R}^N$ (EEG data vector)

1: $H \leftarrow \text{Histogram}()$

2: $\mu_X \leftarrow \text{mean}(X)$, $\sigma_X \leftarrow \text{standard-deviation}(X)$

3: choose k (to determine $\mu_X - k * \sigma_k$ and $\mu_X + k * \sigma_k$)

4: Identify the eye blinks common forms

5: **for** $i = 0$ **to** N

6: Detect P points: $P < (\mu_X - k * \sigma_k)$ **or** $P > (\mu_X + k * \sigma_k)$

7: **end for**

8: Identify the eye blinks non-common forms

9: Remove all the detected eye blinks forms

End

The blinks common form identification is performed by computing, in a first time, the approximate temporal duration of each blink. In a second time, we deduce the approximate temporal duration average, which represents the blinks common form approximate temporal duration for a given subject. Using this common form, we can label an eye blink in an EEG recording. Once a point $P(t_i, v_i)$:

$$(P(t_i, v_i) < (\mu_X - k * \sigma_k) \text{ or } P(t_i, v_i) > (\mu_X + k * \sigma_k))$$

is detected, we search the first point $P(t_j, v_j)$ where $j < i$ and $v_j \approx 0$. When $P(t_j, v_j)$ is identified, we trace the blink common form starting from the instant t_j (Figure.3).

In some instances, it may happen that the subject makes a particular eye movement. This generates particular forms in the EEG recording. To overcome this problem, we decided to adapt the common form identification process in order to find the maximum non-common forms that correspond to blinks.

The data on which the work was conducted, consist of several recordings during the completion of a matrix algebra exercise. The signals acquisition was performed using OpenVibe [6] tool, with a sampling frequency of 512 Hz. The position of the electrode is illustrated in Figure 4.

We decided to work on Fp1 electrode for various reasons:

- From a practical point of view, it allows to set the electrode on the facial skin [4].
- The Fp1 electrode is close to that of the EOG, and can detect therapeutic eye movement.

The approach in this context is to use prior information about signal frequency bands. Given that eye movements include high frequency relative to the EEG signal,

the signal $Fp1$ is filtered using a low pass filter to a 40 Hz cutoff frequency.

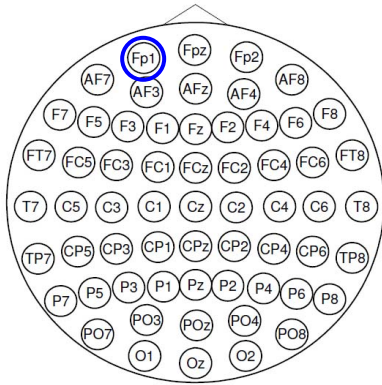


Figure.4: Fp1 electrode in the 10-20 international system

IV. EXPERIMENTATION AND RESULTS

In our application the approach is based on statistical calculations applied to EEG signals recorded by the single-electrode system NeuroSky (Fp1 electrode in the 10-20 system).

A. Protocol and experimentations

EEG data used in this study were recorded on the students of the Department of Mathematics, Computer Science and Biology at the Mohammed First University, Morocco. The population consists of 2 females and 8 males aged between 20 and 30 years old (TABLE I).

The experiments conducted in this study consist of a test, in which, the user must solve a set of matrix products. The difficulty of those products is in an ascending order. EEG data were recorded using the OpenVibetool with a sampling rate of 512 Hz, and applying the filter band-pass 0.5-40 Hz.

B. Results

The obtained results after application of the algorithm presented above are illustrated in Figure.5. To evaluate the performance of the algorithm, we calculated the performance characteristic (ROC curve) to measure the true positive rate depending on false positive rate. The performance characteristic parameters, calculated on all records, are:

TABLE I. PERFORMANCE CHARACTERISTIC PARAMETERS

<u>Recordings</u>	<u>TPR</u>	<u>SPC</u>	<u>PPV</u>
R1	90 %	99.3 %	98.3 %
R2	97.8 %	99.3 %	95.74 %
R3	91.41 %	99.2 %	100 %
R4	100 %	99.1 %	90 %

R5	100 %	97.8 %	78.04 %
R6	92.5 %	97.6 %	88.1 %
R7	94.11 %	97.5 %	84 %
R8	96 %	96.8 %	84.84 %
R9	85.13 %	93.9 %	87.27 %
R10	90 %	90.9 %	71.42 %
Average	93.69%	97.14 %	87.87 %

where :

- TPR : True Positive Rate (or sensitivity).
- SPC : True Negatives Rate (or specificity).
- PPV : Positive Predict Value.

Besides the performance characteristic, we evaluated this algorithm by performing Kapp test (coefficient k) to measure the agreement between the result of detection provided by the algorithm and detection made by the experimenter.

The calculation of k is as follows:

$$k = \frac{P_r(a) - P_r(e)}{1 - P_r(e)} \quad (13)$$

where :

- $P_r(a)$: the agreement rate between the algorithm and the experimenter.
- $P_r(e)$: the probability of a random agreement.

The application of kappato EEG data from our experiments gave us all coefficients k greater than 0.78, which implies a strong agreement between the result of our algorithm and detection made by the experimenter. The obtained coefficients are presented in the TABLE II.

On another hand, we have made a comparison between the result of our algorithm and the parameter "Blink Strength" granted by the Neurosky EEG headset. This parameter provides comparative values on the strength of the eyes' movement. This comparison is presented in Figure.6.

(a)

interface system. Moreover this algorithm could be used to detect eye blinks in an EEG recording, and to transform them into commands to control a BCI system.

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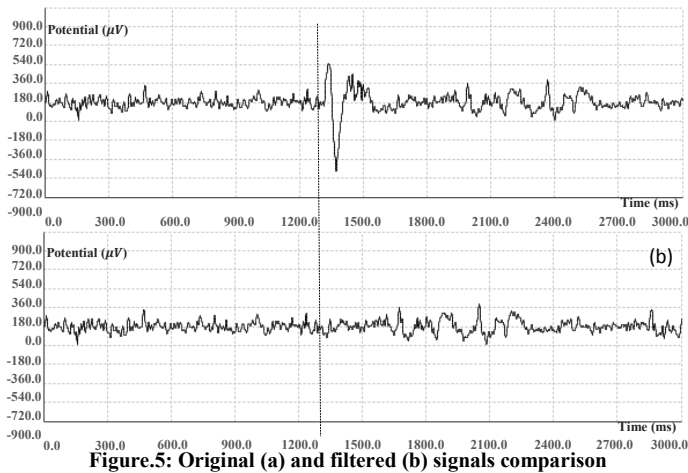


Figure.5: Original (a) and filtered (b) signals comparison

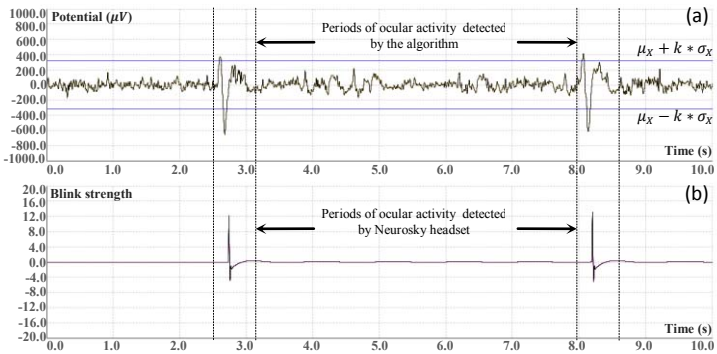


Figure.6: Algorithm result (a) and «Blink Strength» (b) comparison.

TABLE II. KAPPA COEFFICIENTS

Rec's	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	Av
K	0.90	0.95	0.88	0.94	0.86	0.88	0.88	0.89	0.78	0.88	0.88

Conclusion

In recent years, several methods have been developed for the identification and extraction of ocular artifacts from EEG signals. In our algorithm, we show that, in the case of a single electrode, the use of a set of prior information on the wave frequencies, allows to overcome the problem of EEG signals contamination by ocular artifacts. The results we present in this paper allow a future use of this method into a future brain computer