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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 beof 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 andefficiency. In our study we propose a new method to detect and remove blinks. Given theemergent number of embedded systems in relation to the fieldof 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 windowaround$t$:

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

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:

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

According to Gamma law:

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

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):

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

where Γ is Gamma function.

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

Once detecting theocular 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:

$$Y(t) = W^T X(t) \tag{5}$$

B. Blind Sources Separation (BSS)

The aimof blindsource separation(BSS) [1,2]is to recoverthe original sourcesgivenonlysensorobservations. In this approach,we assume thatthe source signalsarrive simultaneouslyon the sensors.Noisemixtureinthiscaseiswrittenas follows:

$$X = AS + N \tag{6}$$

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:

$$Y = TX = TAS + TN \tag{7}$$

where:

$Y$is the estimation of$S$sources(assuming thatthenumberof$N_S$sourcesisequal to the numberofsensors N_C).

BSSalgorithmsseekthe matrix$T$ so thatthe TAproduct is a reducedanda diagonalmatrix. Thereforethe original sourcemay be recoveredexcept their order andamplitude. Estimated sources$Y$ will bepermutedand normalizedto thestandard deviation.

In simulatedsignals, we can validate the results ofBSS usingseparabilityindex(SI). This index iscalculated from$G = TA$ transformation matrixbetween theoriginal sources andtheestimated sources.

The *SI*iscalculated from theabsolute values of theelements of G. The$g_i$line and $g_j$column of the matrix$G$are normalizedforg'_i and g'_jrespectively:

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

We obtain IS_1 and IS_2indexes fromthe resulting matrix $G' \epsilon \mathbb{R}^{N_S \times N_S}$:

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

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

$$IS = \frac{IS_1 + IS_2}{2} \tag{11}$$

The purposeof thecalculationofthe *SI*indexis to measurethe degree to which$G$ is close to apermutation matrix. For a perfectsources recovery, SI =0.

III. ADOPTED MODEL

Ocularartifactis seen as anoisewhichdistorts theEEGsignal (Figure 1), andwhichmay be due tosaccades(very rapid eye movements, around 1000°/s) or due toblinks, which are characterized by verylarge amplitudes (x10 greater than EEG amplitude) (**Figure.1**).

The detection procedure proposed isbased onthe graphical representationof the EEGdata distribution,for each subject, as a histogram. In almostall cases,the histogramwas a Gaussiancloche(**Figure.2**), which allowedusto assume that theEEG signalfollows a NormalGaussian distribution:

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

where:

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

– σ_X^2 : EEG signal variance.

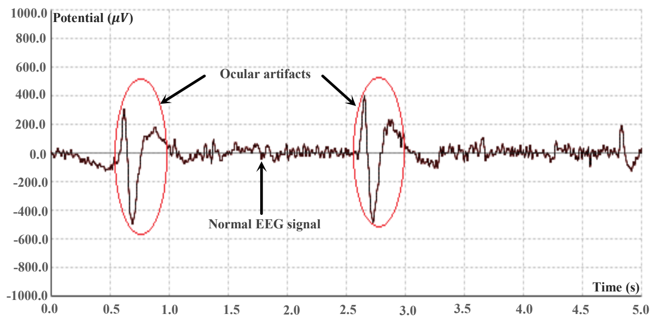

Figure.1 : Example of an ocular artifacts in EEG signal.

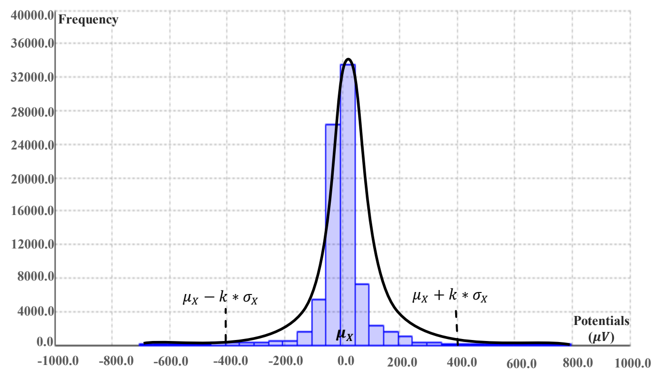

Figure.2 : Histogram example

This hypothesishas given usan idea aboutthe way in whichwe couldidentify timesof ocularartifacts. Indeed,in aGaussian curve, the dominant values, which represent valuesof the EEG,are concentratedaround the mean μ_X. Therarevalues,which represent thelarge amplitudes,are distributedin the ends. These values cancorrespondto ocularartifacts. On the other hand, the interval $I = [\mu_X - k * \sigma_X, \mu_X + k * \sigma_X]$($k \epsilon \mathbb{N}$ and σ_X is the standard deviation), containsa certain percentage ofvalues. In practice, about 65% of the values belong to the interval I for $k = 2$. In our application,we have chosen tovary (from $k = 1$ to $k = 5$ theparameter $k$in different casesprocessedEEGdata series. The interval$I$allows to setthe boundsfrom which wecan knowwhether a givenvalueisan artifactor not (Figure.3).

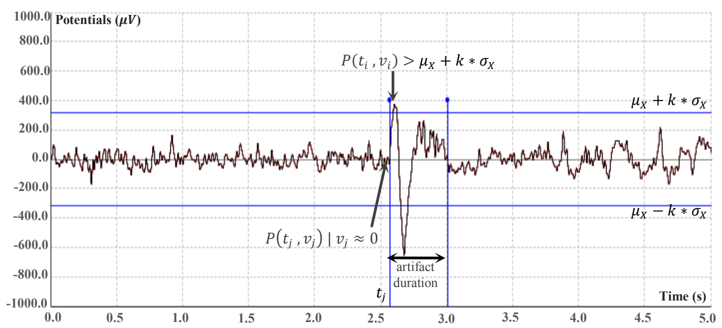

Figure.3: Detection of ocular artifacts instants.

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

Algorithm *Blinks detection& elimination*

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

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

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

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

4: Identify the eye blinks common forms

5: **for** $\boldsymbol{i = 0}$ **to** $\boldsymbol{N}$

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

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 $P(t_i, v_i)$:

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

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 whichthe workwas conducted, consist of severalrecordings duringthe completion of amatrix algebra exercise. The signals acquisition wasperformed usingOpenVibe [6]tool,witha sampling frequencyof512Hz. Thepositionof the electrode isillustratedin Figure 4.

We decided towork onFp1electrodefor various reasons:

- From a practical pointof view, it allows to setthe electrode on thefacial skin [4].
- TheFp1electrodeisclose to that oftheEOG, andcan detecttherapid eye movement.

The approachin thiscontext is touseprior informationaboutsignalfrequency bands. Giventhat eye movementsincludehigh frequencyrelative to theEEGsignal, thesignalFp1is filteredusinga low passfiltertoa40 Hzcutoff frequency.

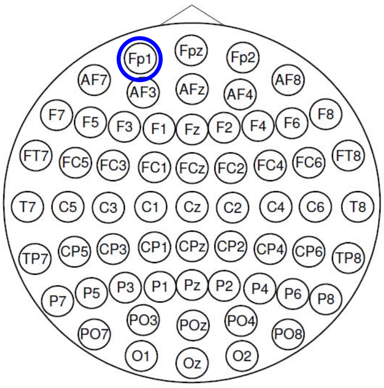

Figure.4: Fp1electrodein the 10-20 international system

IV. EXPERIMENTATION AND RESULTS

In our applicationthe approach is basedon statistical calculationsapplied toEEGsignals recorded by thesingle-electrode systemNeuroSky (Fp1electrode in the 10-20 system).

A. Protocol and experimentations

EEGdata usedin this studywere recorded onthe studentsof the Departmentsof Mathematics, Computer Science andBiology at the Mohammed FirstUniversity, Morocco. Thepopulation consists of2 females and8malesagedbetween 20 and 30years old (**TABLE I**).

The experiments conductedin this studyconsist of a test,in which, the user must solve aset ofmatrix products. The difficulty of those products is in anascending order. EEGdata were recordedusing theOpenVibetool witha sampling rateof 512Hz,and applyingthe filterband-pass0.5-40Hz.

B. Results

The obtainedresults after application of thealgorithmpresented aboveare illustratedin **Figure.5**. To evaluate the performanceof the algorithm, we calculated the *performance characteristic* (*ROC* curve)to measure thetrue positive rate depending on false positive rate. The performance characteristic parameters, calculated on all records, are:

TABLE I. PERFORMANCE CHARACTERISTIC PARAMETERS

Recordings	***TPR***	***SPC***	***PPV***
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.

Besidesthe performance characteristic, we evaluated thisalgorithmby performingKappatest (coefficient k) to measure the agreement betweenthe result of detectionprovided bythe algorithm anddetection made bythe experimenter.

The calculationofkisas follows:

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

where :

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

The application ofkappato EEGdata from ourexperimentsgave usallcoefficients kgreater than 0.78, which implies a strong agreementbetween the result ofour algorithm anddetection made bythe experimenter. The obtained coefficients are presentedintheTABLE II.

On anotherhand, we havemade a comparisonbetween the resultof our algorithmand the parameter“Blink Strength” granted by theNeuroskyEEGheadset. This parameterprovides comparativevalues on thestrength of the eyes’ movement. This comparison is presented in **Figure.6**.

(a)

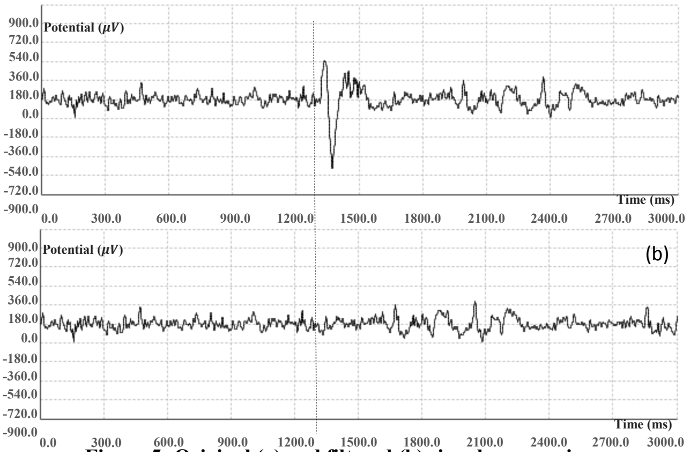

Figure.5: Original (a) and filtered (b) signals comparison

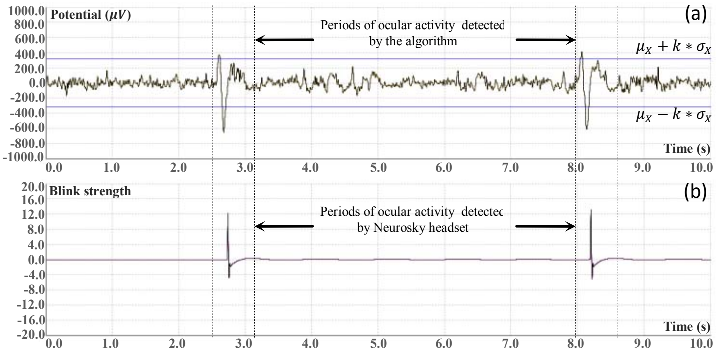

Figure.6:Algorithm result (a) and«*Blink Strength*» (b) comparison.

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 methodshave been developed forthe identificationandextractionof ocularartifacts fromEEGsignals. Inouralgorithm, we show that, inthecase of a singleelectrode, the use of aset ofprior information onthe wavefrequencies, allows to overcometheproblem 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 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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