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Eye Blink Detection Using a Support Vector Machine Classifier

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***Abstract*—In the last years, several applications for Brain Computer Interfaces (BCI) have been proposed, based on different kind of EEG features (e.g., mental states, cognitive load, alertness and eye blinks). Since eye blinks are considered artifacts for EEG when other EEG features are analyzed, many studies are focused on the detection of spontaneous eye blinks for removing. Only a few papers have investigated voluntary eye blinks classification, and most of them using different sensing techniques to EEG (Electrooculogram (EOG), Magnetic Resonance Imaging (MRI)). Toward development of a BCI application, the aim of this paper is to classify intentional eye blink events from EEG signals, to employ them as command controls in BCI applications, for people with special needs. In this paper, we trained a Support Vector Machine Classifier based on statistical features. The dataset is acquired using the low-cost Emotiv EPOC headset, using only a single EEG electrode through an experiment with a visual marker for 12 subjects.**

Keywords-Voluntary eye blink classification; support vector machine; statistical features; BCI;

I. Introduction

Amyotrophic lateral sclerosis (ALS) is a lethal, degenerative and neurological disease characterized by chronical deterioration and death of efferent neurons, this disease has no cure. Although this disorder decreases the function of muscles and nerves, in most cases it does not affect the patient´s mind, senses and some internal organs. Eventually ALS affects the voluntary muscles in the body and produces paralysis, but usually the patients maintain the control of eye muscles, therefore they can produce voluntary eye blinks.

In general an eye blink has two peaks: positive and negative. An open eye event is related to a negative peak while close eye event produces a positive peak in EEG. Eye blinks can be classified in three categories: spontaneous eye blink, reflexive eye blink, and voluntary eye blink. Spontaneous eye blink occurs frequently, reflexive eye blink occurs when an external stimulus suddenly appears near the eyeball and produces a defensive reaction blink in a subject, and voluntary eye blink is caused by intentional eye closing [1]. Spontaneous eye blink frequency is about to ten and twenty times per minute without external stimuli, this event occurs due to the natural function to clean, lubricate and oxygen the cornea [2].

In a BCI application based on eye blinks, it is important to discriminate voluntary eye blinks from the spontaneous blink, because it is not practical for users, to keep theirs eye opened until they need to take a decision control. Then, the aim of this project is to develop an application to classify voluntary eye blinks and spontaneous eye blinks. Three different scenarios have been studied for classification, using a SVM classifier based on statistical features.

There are different methods to detect eye blinks in EEG signals, such as blind source separation [3], Support Vector Machine (SVM)-Adaptive Boost (AdaBoost) [4], and Neural Network [2-5]. A few previous works have studied intentional eye blink classification (e.g., Magnetic Resonance Imaging (MRI) [6] and EOG techniques [7, 2]). Voluntary eye blinks have been analyzed using EEG in [8-10].

II. Methodology

A. *Data Acquisition Procedure*

The Emotiv EPOC™ headset developed by Emotiv Systems was used to sense the EEG signals. This device contains 14 electrodes plus 2 references with fixed positions. The electrodes are located (based on the international 10-20 system) at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8,AF4, with CMS/DRL references in the P3/P4 locations and with digital notch filters at 50 Hz and 60 Hz [11]. The EEG data were acquired from 12 healthy subjects (18-28 age group). The signal is sampled at 128 Hz. A 1st order IIR Butterworth High-pass filter at 0.16 Hz is applied to EEG signals for removing the Direct Current (DC) offset. Since in the pair AF3-AF4 the eye blink effects are clearly evident, the size of the data was reduced to a single channel: AF3.

In Fig. 1 and Fig. 2, spontaneous and voluntary eye blink trials are displayed respectively. These trials were randomly taken from the data set acquired. As it is seen, the spontaneous blink signal has a duration less than 0.5 s (including positive and negative peaks). Otherwise, for the voluntary blink case, the event signal has a duration less than 1 s. Hence, we decided to set the sample window in 1 s (128 samples). The recording time for each subject was 120 s (15360 samples) and it was divided into 120 sample windows of 1s. Therefore, the entire signal has 1440 sample windows.

The data tests were acquired in 2 blocks of 60 s each one. For the first block of 60 s, subjects were asked to relax and focus their eyes in a white rectangular figure displayed on a monitor and to blink normally when they needed it, subjects were in a sitting position and the monitor was in front of them. For the second block, we asked them to blink once only when the rectangular figure had a color change (from white to blue), and applying a very little force to emphasize the intention. Fig. 3 shows the experiment procedure for one subject. 25 blue rectangular figures appeared in that second block of 60s for each participant. Once we recorded the 2 blocks for every subject, we identified the events by inspection. We identified two events in the first block and we called open eyes (O) and spontaneous eye blink (S). Moreover, in the second block we selected also two events and we called open eyes (O) and voluntary eye blinks (V). There are a different number of spontaneous eye blink events in the first block for each subject because it depends on the subject´s need to blink, but second blocks had 25 predetermined voluntary eye blinks events for each subject. The little effort applied in the voluntary eye blink events causes a variation in amplitude and duration, as seen in Fig. 1 and Fig. 2.

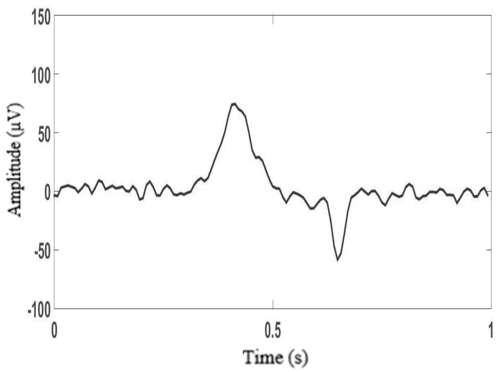

Figure 1. Spontaneous eye blink trial from EEG.

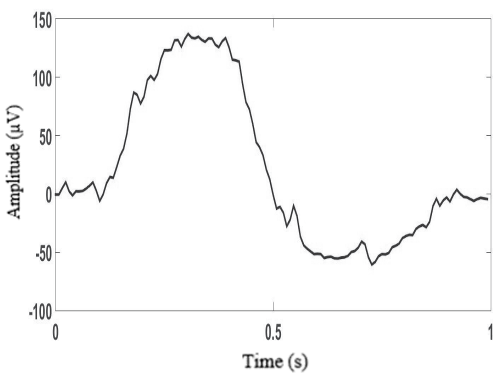

Figure 2. Voluntary eye blink trial from EEG.

B. Features

Statistical characteristics were taken from EEG signals to feed the Neural Network Classifier. The features used are: Max value, Min value, Mean Value, Variance, Standard Deviation, Skewness and Kurtosis. These features were obtained for each sample window from the 12 subjects (1440 samples). We structured the 1440 feature data in a 12x120 matrix, rows symbolize subjects and columns represent recorded sample windows for each subject.

$$\text{Max value} = \max[x] \tag{1}$$

$$\text{Min value} = \min[x] \tag{2}$$

$$\text{Mean} = \frac{1}{L}\sum_{n=1}^{L} x_n \tag{3}$$

$$\text{Variance} = E\left((x-\mu)^2\right) \tag{4}$$

$$\text{Standard Deviation} = E\left(\sqrt{(x-\mu)^2}\right) \tag{5}$$

$$\text{Skewness} = E\left(\left(\frac{x-\mu}{\sigma}\right)^3\right) \tag{6}$$

$$\text{Kurtosis} = E\left(\left(\frac{x-\mu}{\sigma}\right)^4\right) \tag{7}$$

Mean value parameter (μ) is the arithmetic mean of one sample window (Eq. 3) Variance is the 2nd-order central probabilistic moment (Eq. 4) and the standard deviation (σ) is the square root of the variance, which measures the dispersion around the average (Eq. 5). Skewness is the 3erd-order central probabilistic moment and it describes the symmetry around the mean value (Eq. 6). Kurtosis coefficient is the 4th-order central probabilistic moment (Eq. 7).

Figure 3. Data acquisition procedure

C. Support Vector Machine

A SVM is a classifier based on the use of hyperplanes to discriminate two or more classes. It is a learning tool originated in modern statistical learning theory and it was invented by Vladimir Vapnik [12]. An optimal hyperplane in SVM maxims the margin between classes and generalize the learning process for classification. For linear classification, when the classes are classified using linear decisions, there exists a linear function for the SVM´s hyperplane of the form:

$$f(x) = w^T x + b \tag{8}$$

On the order hand, for non-linear classification, there exists a non-linear function for the optimal hyperplane in the classifier.

$$f(x) = w^T \phi(x) + b \tag{9}$$

Ec. 9 is linear for the map data $\phi(x)$ but it is non-linear for the original data *x*, where $x \in R^n$. According to the representer theorem [13], *w* is defined as:

$$w = \sum_{i=1}^{m} \alpha_i \phi(x_i) \tag{10}$$

By using Lagrange transform, the optimal decision rule is *sign* (*f(x)*), where:

$$f(x) = \sum_{i=1}^{m} \alpha_i \phi(x_i) \cdot \phi(x) + b = \sum_{i=1}^{m} \alpha_i K(x_i, x) + b \tag{11}$$

$K(x_i, x)$ is known as Kernel function.

In this work we used 3 Kernel functions: Linear, Quadratic and Cubic. Table I shows the Kernel´s equation.

TABLE I. KERNELS USED

Kernel	***Equation***
Linear	$K(x_i, x)$
Quadratic	$K(x_i, x) = (x_i, x+1)^2$
Cubic	$K(x_i, x) = (x_i, x+1)^3$

III. RESULTS AND DISCUSSION

A. *Kruskal-Wallis Statistical Test*

Kruskal-Wallis statistical test was used to detect statistical significance in the features extracted for the three classes previously defined: O, S and V.

According to the results, the three classes are statically significant for each feature, because they have small p-values (*p-value* < 0.05)

B. *Classification Cases.*

In this work we analyze three discrimination cases:

V-S-O, open eyes (O), spontaneous eye blink (S) and voluntary eye blink (V) events are classified. Three classes were compared.

V-OS, open eyes class-spontaneous eye blink (OS) and voluntary eye blink (V) events are categorized. Two classes were classified

V-S, spontaneous eye blink (S) and voluntary eye blink (V) events are discriminated. In this case we ignored the Open eye blink events, then the data set changed its length because we removed the sample windows where O event appeared. Two classes where matched.

C. *Performance Analysis*

The performance analysis of the classifier results was analyzed calculating 3 parameters: Sensitivity, Specificity and Accuracy. From Ec. 8, Ec. 9 and Ec. 10, TP: True Positives, TN: True Negatives, FP: False Positives and FN: False Negatives.

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% \tag{8}$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \tag{9}$$

$$Specificity = \frac{TN}{TN + FP} \times 100\% \tag{10}$$

Accuracy, Sensitivity and Specificity are used to evaluate the performance of a supervised learning. Accuracy is the overall effectiveness of a classifier, Sensitivity if the effectiveness of a classifier to identify positive labels and Specificity indicates how effectively a classifier identifies negative labels [14].

D. *Classification Performance*

TABLE II. PERFORMANCE ANALYSIS OF CLASSIFICATION EXPERIMENTS

Experiment	**SVM Performance**			
	Kernel	***Accuracy***	***Sensitivity***	***Specificity***
V-S-O	Linear	89.79%	87.38% 73.16% 93.89%	96.75% 95.68% 88.59%
	Quadratic	**91.18%**	87.67% 78.13% 94.94%	96.75% 96.55% 90.45%
	Cubic	90.90%	89.72% 74.40% 94.85%	95.94% 96.84% 90.80%
V-OS	Linear	94.51%	89.89%	95.61%
	Quadratic	94.65%	87.54%	96.50%
	Cubic	**95.14%**	88.59%	96.85%
V-S	Linear	**91.89%**	94.83%	87.68%
	Quadratic	91.68%	90%	92.74%
	Cubic	91.28%	92.98%	88.66%

V: Voluntary, S: Spontaneous and O: Open eyes events.

IV. DISCUSSION

According to Table II. The best result in V-S-O experiment was achieved using a quadratic kernel. On the other hand, for the V-OS case, the best accuracy was obtained by a cubic kernel, and finally for the V-S classification, a linear kernel was enough for the best result. It would be interesting design another algorithm as Artificial Neural Network for these cases and then compare the results with the obtained in this work.

V. CONCLUSION

In this paper, we proposed a novel application based on a support vector machine classifier to classify voluntary eye blinks using only a single EEG signal channel (AF3). Test accuracy for almost all classification cases was greater than 90%, except the V-S-O case, where the linear SVM reached an 89.80%. Linear kernel obtained the best accuracy for the V-S case, cubic kernel for the V-OS scenario, and the V-S-O experiment obtained the best accuracy using the quadratic kernel. Future work is focused on developing an online detection.

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