Algorithm to detect six basic commands by the analysis of
electroencephalographic and electrooculographic signals

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Abstract—The Electroencephalographic signals are com-
monly used for developing brain-machine interfaces (BMI),
in fact is the most used biological signal to translate brain's
commands to the computer. Some additional physiological
measures have been used along with EEG in order to obtain
more robust and more accurate BMI systems. However, since
very sophisticated recording devices are more available, signal
processing is getting complicated, mainly due to the invested
computational time in signal extraction and pattern recognition.
Therefore, processing time in BMI could be too long, which is
useless for some applications, for instance, devices used in
rehabilitation engineering, or some robotic systems. In this
paper, we propose a six commands recognition algorithm using
only one EEG bipolar connection (O1-P3) in combination
with bilateral electrooculographic signals. Our algorithm
could identify these six commands based on simple temporal analysis
with an average recognition accuracy of 97.1% for the selected
sample of subjects. The average recognition time do not last
more than 0.5 seconds after one of the events occurred.

I. INTRODUCTION

The development of brain-machine interfaces (BMI) has
had a significant growth over the last decade, fascinating
researchers all over the world have been reported [1]–[9]. In
each of these publications, it has been exposed the impor-
tance of BMI development, considering that such technique
could be applied in a wide variety of fields, ranging from
entertainment (videogames) [2], [3], to biomedical devices
such as prosthetics and orthotics [1], [4]–[9].

Perhaps the main instrument for the development of BMI
is the electroencephalogram (EEG). The EEG is a measure
of time-varying potentials caused by systematic neural activities
in the brain [10]. In the last years, EEG signals were
used as reliable indicators of the state of brain activities in
order to develop BMI [11], [12]. The advantage of using
electroencephalographic signals is that EEG is a noninvasive
 technique that provides useful information about the brain
activity [13]. Moreover, EEG is more accessible than other
acquisition devices used in BMIs, such as near infrared (NIR)
or magnetic resonance imaging (MRI). In addition, it is
relatively tolerant to subjects’ movement under controlled
conditions or by the use of noise cancellation algorithms.

Conversely, additional physiological measures are used to
improve the efficiency and robustness of BMI systems [13],
[14]. Nowadays, electrooculogram (EOG) is a physiological

measure commonly used for human-machine interfaces and
human-computer interfaces [14]–[16]. Therefore, the use of
EEG signals, together with EOG signals, could be very
helpful to create high-quality BMI [17].

Previous works in BMI systems indicates that the signal
acquisition and processing are getting complicated since
more sophisticated recording devices are more available [11].
Although these sophisticated devices help developing an ac-
curate BMI, it is worth to remark that there is not an standard
algorithm since many pattern-classification algorithms have
been used in the design and development of BMI [18]. If the
signal acquisition and processing are too complicated, then
the processing time will be greater, and the BMI will not be
useful for some applications, such as prosthetic devices or
orthotics. In this paper, we propose a six commands recogni-
tion algorithm that could be used for BMI applications. For
this algorithm, we used EOG in a similar way as is presented
in [19], and only one EEG bipolar connection (O1-P3). In
comparison to other EEG eyes closed-open recognition
algorithms, such as [20], in which the average recognition
time is 0.38 seconds, the accuracy of the algorithm presented
in this paper is better, having an average recognition accuracy
of 97.5% compared to the 93% showed in [20], when only
one bipolar derivation is used. The advantage is that the
processing time do not last more than 0.5 seconds, since
the six commands classifier, which is a simple algorithm,
only requires the raw EOG signal from both eyes, and the
EEG short-time Fourier Transform (STFT) as inputs. That
the EOG signal does not need to be processed to be used
by the classifier is a great advantage, since it requires less
computational work, considering it has a high average of
recognition accuracy (96.7%) compared to other recognition
algorithms that need to treat the signal (94.1% for [19]
and 93.2% for [21]). Moreover, an algorithm that detects
six commands could be used for multiple applications, such as:

This paper is divided as follows: a first section where
methodology about subjects’ conditions, the experiment set
up and the signal analysis are described. A second section
where the identification of simple commands (eyes up, down,
left, right, eyes closed and eyes open) is carried out by the
proposed algorithm, using EEG and EOG signals obtained
from male subjects. Finally a section with conclusion and
future work description is included.
II. METHODOLOGY

A. Subjects

A total of 4 male subjects, right handed volunteers in the age group of 21 to 22 years (20 ± 0.58) with no prior history of nervous system disorder. EEG and EOG tests were performed simultaneously in the Lab. Environmental conditions as illumination and noise were controlled. During the placement of the electrodes, subjects were told about the purpose of the study.

B. Electrode Placement

The EEG electrodes were placed on the scalp according to the international 10-20 system [22]. However, we used only one bipolar connection: O1-P3. For the EOG, we placed two electrodes for the right eye, SE2 (Superior-Eye) and LE2 (Lateral-Eye), and two electrodes for the left eye, SE1 and LE1. The electrode positions for the EEG and EOG are shown in Figure 1. Note that both, EEG and EOG have an extra electrode: G (Ground, 1 for left earlobe and 2 for the right earlobe). G1 was used as the EEG ground, and G2 as the EOG ground for both eyes.

![Electrode positions](image)

**C. Experimental Paradigm**

Two types of experiments were carried out for each subject, each of them are described following.

1) Experiment 1, position:

This experiment includes 3 sections: eyes-open for 10 seconds, eyes-closed for 10 seconds and eye movements (up, down, left and right). First, the subjects were asked to seat comfortable with their eyes closed, a basal register is carried out. Subjects were told to open their eyes when they heard the word "open", which was said after 10 seconds of recording eyes-closed activity. After 10 seconds of recording eyes-open activity, subjects were told to move their eyes in this order: up, up, down, down, left, left, right, and right; with a lapse of two seconds between each eye movement. It is worth to remark that after each eyes movement, subjects were previously instructed to put their eyes in normal position (central position) before continuing with the sequence.

2) Experiment 2, open and closed:

This experiment has the same 3 sections as Experiment 1. It was performed to each subject changing the first 10 seconds to eyes-open. Then, after 10 seconds of eyes-open recording, subjects were asked to close their eyes. Finally, after 10 seconds of closing their eyes, subjects were told to open their eyes again to start the same eye movements activity as the one made in the Experiment 1.

D. Data Acquisition

The EEG signal and EOG signals were recorded using a four channel commercial data acquisition device, BIOPAC MP35®, manufactured by BIOPAC Systems, Inc (http://www.biopac.com/). Only three of the four channels were used during the experiment. Two of them were used to record the EOG signal of both eyes and the other one was used to record the EEG bipolar connection: O1-P1. EEG signal was recorded at 200 samples/sec with a 0.5-35 Hz digital filter. EOG signals were recorded at 200 samples/sec with a 0.05-35 Hz digital filter. The signals were recorded using the BIOPAC MP35 software. However, they were saved for further processing using Matlab®.

E. Signal Processing

Since the EOG raw signal was very manageable, this signal was not processed and it was used as the input of the eye movements classifier. However, the EEG signal was filtered using a band-pass filter with the low-pass and high-pass cut-off frequencies to be 8 Hz and 13 Hz, respectively. This filtering leaves only the alpha wave generated by the O1-P1 bipolar connection. After obtaining the alpha wave, we used Short-Time Fourier Transform (STFT) with a 500 milliseconds rectangular window. We decided to use a 500 ms rectangular window due to the fact that sampling frequency of the signal was 200 samples/sec. Hence, 500 ms have 100 samples, which is enough data for a signal with frequency components up to 30 Hz. If a rectangular window of less than 500 ms is used, data would not be enough for an acceptable analysis because the STFT of the EEG alpha wave may have very poor resolution. On the other hand, rectangular windows with more than 500 ms could be used; however, since we have obtained accurate results from a 500 ms window, it is not necessary to use a window that will make the signal processing last longer. The data obtained by the STFT was the input of the eyes closed-open classifier.

F. Classifier

In order to determine the events: eyes-closed, eyes-open and eye movements (up, down, left, and right), we proposed two different classifiers: Eyes Closed-Open Classifier and Eye Movements Classifier, which are described as follows:
1) Eyes Closed-Open Classifier: The EEG alpha wave \( \text{eeg}(t) \) was obtained by filtering the EEG raw signal with a 8-13 Hz filter band-pass. The STFT of \( \text{eeg}(t) \) is the input for this classifier. The STFT of \( \text{eeg}(t) \) is given by:

\[
\text{EEG}(t, \tau) = \int_{-\infty}^{\infty} \text{eeg}(t)w(t - \tau)e^{-j\omega t} dt
\]

where \( \text{STFT}\{\text{eeg}(t)\} \equiv \text{EEG}(t, \tau) \), \( w(t) \) is the window function, and \( \text{eeg}(t) \) is the EEG alpha wave.

By analyzing the results of Equation (1), as will be shown in the results section, we realized that the magnitude values when eyes were open were about 10%-20% the values obtained when eyes were closed. Therefore we decided to use a threshold to classify if eyes were open or closed.

For the threshold, after we obtained the absolute value of \( \text{EEG}(t, \tau) \), we get its maximum magnitude value \( (\text{Y}_{\text{max}}) \):

\[
\text{Y}_{\text{max}} = \max(\text{EEG}(t, \tau))
\]

Then, we compare \( \text{Y}_{\text{max}} \) with the maximum magnitude value of each 500 ms window \( (\text{Y}_{i}) \), and the decision whether the subjects have their eyes closed or open was made by the following logical inference system:

\[
\text{Y}_{i} \geq 0.35\text{Y}_{\text{max}} \rightarrow \text{eyes-closed} \\
\land \text{Y}_{i} \geq 0.35\text{Y}_{\text{max}} \rightarrow \text{eyes-open}
\]

i.e., if the maximum magnitude value of a 500 ms window is greater than the 35% of the maximum magnitude value of \( \text{EEG}(t, \tau) \) then this means the subject has his eyes open, otherwise the subject has his eyes closed. Of course it means that before using this algorithm for on-line applications, it is necessary to obtain a preliminary register in order to "calibrate" the algorithm for its further use.

2) Eye Movements Classifier: The EOG bilateral raw signals are the inputs for this classifier. As will be exposed in the results section and as has been proved by [19], changes in the EOG signal amplitude, either positive or negative changes, determine when an event occurred. When Event "a" occurred (Event "a" stands for eyes moved up) both signals’ amplitude increased dramatically. On the other hand, when Event "b" occurred (Event "b" stands for eyes moved down) both signals’ amplitude decreased significantly. When Event "c" occurred (Event "c" stands for eyes moved left) left eye EOG signal \( \text{leog}(t) \) decreased in magnitude and right eye EOG signal \( \text{reog}(t) \) increased. Conversely, when Event "d" occurred (Event "d" stands for eyes moved right) \( \text{leog}(t) \) magnitude increased and \( \text{reog}(t) \) magnitude decreased. For this classifier, an amplitude threshold was used to determine if an event, of any kind, occurred. First, we obtained the maximum amplitude value as well as the minimum amplitude value of both EOG signals:

\[
\text{leog}_{\text{max}} = \max(\text{leog}(t)) \quad (3) \\
\text{leog}_{\text{min}} = \min(\text{leog}(t)) \quad (4) \\
\text{reog}_{\text{max}} = \max(\text{reog}(t)) \quad (5) \\
\text{reog}_{\text{min}} = \min(\text{reog}(t)) \quad (6)
\]

Then, for the eye movement classifier, we used the following logical inference system:

\[
[\text{leog}(t_{0}) \land \text{leog}(t_{0} + 250\text{ms})] \geq 0.3\text{leog}_{\text{max}} \quad \rightarrow \text{Event a} \\
[\text{leog}(t_{0}) \land \text{reog}(t_{0} + 250\text{ms})] \geq 0.3\text{reog}_{\text{max}} \quad \rightarrow \text{Event a} \\
\text{leog}(t_{0}) \leq 0.3\text{leog}_{\text{min}} \land \text{reog}(t_{0}) \leq 0.3\text{reog}_{\text{min}} \quad \rightarrow \text{Event b} \\
\text{leog}(t_{0}) \leq 0.3\text{leog}_{\text{min}} \land \text{reog}(t_{0}) \geq 0.3\text{reog}_{\text{max}} \quad \rightarrow \text{Event c} \\
\text{leog}(t_{0}) \geq 0.3\text{leog}_{\text{max}} \land \text{reog}(t_{0}) \leq 0.3\text{reog}_{\text{min}} \quad \rightarrow \text{Event d}
\]

where \( t_{0} \) is any time within the signal.

Notice that in the EOG classifier the 30% of the maximum magnitude, as well as the 30% of the minimum magnitude, are used as thresholds for identifying events. Unlike the EEG classifier that uses the 35% of the maximum magnitude as threshold. It is also important to realize that in order to classify Event "a", there are two extra conditions. This conditions were thought to avoid identifying Event "e" (Event "e" being an involuntary blinking) as Event "a", since both events are very similar. However, since the amplitude increment last about 500 ms in Event "a" and approximately 200 ms in Event "e", if the signal amplitude reaches the threshold more than 250 ms it will be classify as Event "a", otherwise it would not be classify as an event; since the signal increased due to an involuntary blink.

III. RESULTS AND DISCUSSION

In order to show the effectiveness of the proposed algorithms we present in this section the results obtained for one of the subjects. Similar results were obtained for the others. Figure 2 shows the EOG signal recorded from one subject when he performed the eye movement activity. Recall that the letters assigned to each event, letters that are pointing to an event of the EOG signal, stand for:

a. Eyes up. 
b. Eyes down. 
c. Eyes left. 
d. Eyes right. 
e. Involuntary blinking.

Figure 3. a. shows the EEG signal, recorded from Experiment 1, filtered with the 8-13 Hz band-pass filter to obtain the alpha wave components. Figure 3. b. shows the STFT of the EEG filtered signal, where the magnitude of each frequency component ranges from white (for the maximum magnitude) to black (for the minimum magnitude) in a gray scale. The graphs obtained from Experiment 2 are shown in Figure 4. Letters of the graphs in Figure 3 and 4, pointing to an event, stand for:

a. Eyes open. 
b. Eyes closed.
It is easy to see how the amplitude of the EEG alpha wave decreases when eyes are open and increases when eyes are closed (see Figure 3. a. and Figure 4. a.). The EEG short-time Fourier Transform is further evidence of the changes in magnitude of the frequency components of the signal between 8 and 13 Hz when eyes are open and closed (see Figure 3. b. and Figure 4. b.).

In Figure 5, we present a fragment of the EEG alpha wave showed in Figure 3. a. In the interval where the signal is marked, from 12 to 12.5 seconds, the classifier identified that the subject had open his eyes. At this interval, we can see a dramatic change in the amplitude of the EEG alpha wave, which actually means the subject has opened his eyes. Figures 6. a. and 6. b. are fragments of the EEG alpha wave showed in Figure 4. a. In Figure 6. a., we can see how an important increment in the alpha wave amplitude is correctly identify by the classifier as the event when the subject closed his eyes. Similarly, Figure 6. b. shows that the event when the subject open his eyes was correctly classify when the EEG alpha wave amplitude decreased.
The percentages of accuracy obtained from both classifiers for the experimental sample are shown in Table I. This recognition rate was calculated by taking in consideration three trials for each subject, that is, three trials for Experiment 1 (position) and three for Experiment 2 (open and closed); each trial carried out as explained in the Experimental Paradigm section. The EEG classifier percentage was obtained by counting how many times the signal entered the classifier and how many of those times the events were classify correctly. For example, a 10 seconds signal will enter the classifier 20 times, since the signal is analized every 500 ms. Therefore, if the subject has his eyes closed the first 5 seconds and open his eyes the last 5 seconds, then, the classifier must categorize the first 10 events as eyes closed and the last 10 events as eyes open. The EOG classifier percentage was obtained by counting the number of times that the signal amplitude exceed the threshold. Similarly to the EEG classifier, we counted the number of times that the events were correctly identified. The high percentage of accuracy from both classifiers shows that a simple logical inference system was enough for a quality six simple command system (eyes moved up, down, left, right, eyes open and eyes closed).

IV. CONCLUSIONS AND FUTURE WORK

A. Conclusion

A hybrid EEG-EOG system to detect six different basic commands for BMI applications is proposed. Therefore, the system objective is to detect the following commands: eyes moved up, down, left, right, eyes were closed and eyes were open. It is important to remember that both classifiers were based only on logical conditions, and, in both cases, analysis was carried out-of-line after a preliminary calibration stage. However, we showed that this is a good alternative for developing BMI since the accuracy results, considering the four subjects and for both classifiers, were not below 94%, and the average recognition time did not last more than 0.5 seconds after one of the events occurred. Pattern recognition was mainly focused on temporal characteristics of the EOG signals, and for the EEG signal, frequency decomposition by STFT was used. After obtaining its STFT, it was possible to classify events by simple temporal analysis.

B. Future work

We have been working in parallel with the design and construction of a portable system to implement this experimental set-up, one EEG channel and two EOG channels. Once we have proved that it is feasible to propose a logical algorithm based on temporal analysis, we will look for its programing in an embedded system. An extension of the number of subjects to test the platform must be done, overall considering on-line and real time applications. In this sense, the platform will be tested under variation of the environmental conditions. Once the accuracy of the algorithm has been proved under these conditions, the use of the algorithm for a practical application could be done. We have been thinking of using the algorithm to drive a wheelchair where its position could be changed by moving the eyes to the left or to the right (EOG classifier: Event c and d, respectively). Moreover, the velocity of the wheelchair could vary depending if the eyes move up or down (EOG classifier: Event a and b, respectively). Closing the eyes voluntarily by a certain amount of time (EEG classifier: Event b) could be used to turn on and off the wheelchair’s motor.

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REFERENCES


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