Improving Communication Efficiency for gaze independent P300 based Brain Computer Interface

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Abstract—This work presents the fusion of a gaze independent P300-based Brain Computer Interface with an asynchronous classifier. The latter can automatically adapt the speed of selection depending on the user psychophysical state and avoid misclassifications when the signal is not reliable enough. Preliminary findings suggest that these features can significantly improve communication efficiency in terms of classification accuracy and errors recovery.

Keywords—BCI, EEG, Asynchronous classifier, efficiency metric.

I. INTRODUCTION

The Brain Computer Interface (BCI) systems provide an alternative and augmentative communication channel for people suffering from severe neuromuscular disabilities. Since some pathologies can affect the control of eye movements, recently there was a growing interest for gaze independent paradigms based on the P300 potential [1-3]. The latter is a cognitive event related potential (ERP) which appears as a positive deflection in the electroencephalographic (EEG) signal about 250-500 ms after the subject recognizes a relevant stimulus between a train of frequent stimuli. In the current study, we explored the combination of the gaze independent P300 Speller described in [1] with an asynchronous classifier previously validated with the Farwell and Donchin's Speller [4] in overt attention conditions [5]. Also we assessed the communication efficiency of the asynchronous system and we compared it to the efficiency of a classical synchronous classifier.

II. MATERIAL AND METHODS

A. Experimental Protocol

Nine healthy participants (mean age= 26.4 ± 4.4) were enrolled in the study. All of them had previous experience with the gaze independent BCI-GeoSpell.

Scalp EEG signals were recorded from 8 positions (Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8; sampling rate 256 Hz). The asynchronous classifier consists in the introduction of a threshold on the score values, being the threshold values defined by means of a procedure relying on ROC curves [5]. Every time the threshold is exceeded a classification occurs, so that the number of stimuli needed to achieve a selection is dynamically adapted. If the threshold value is not reached after a well-defined number of stimuli repetitions, the system abstains from make a selection and a new trial begins (abstention). Each subject completed 2 recording sessions defined as offline and online session respectively. During the former, subjects performed 8 runs of 6 trials each. During the first 6 runs called Control Runs all the 36 characters of the GeoSpell interface were presented as Targets to the subject, who had to focus his attention on it mentally counting the number of its occurrences always gazing to the fixation cross in the middle of the interface. During a trial, which corresponds to the selection of a single character, 10 stimulation sequences were delivered. The last 2 runs were defined as No-Control Runs. During the first No-Control run the subjects were required to fixate the cross in the center of the interface, trying to ignore the surrounding stimulations; during the last No-Control run subjects were also required to perform simple mathematic computations. The online session was composed of a total of 4 runs; in the first 2 runs online classification was carried out by the synchronous classifier, while in the last 2 runs the asynchronous classifier was used. During the online session subjects were required to spell two made sense Italian words of 6 characters each in both synchronous and asynchronous modality.

B. Offline analysis

Data from the offline session was used to choose the best parameters set for the on-line session. The EEG signal was first band pass filtered (0.1-20Hz) using a 4th order Butterworth filter and then it was divided into 800ms epochs starting with the onset of each stimulus. Epoch decimation was carried out segmenting data into blocks having length equal to 12 samples. The mean of these blocks was calculated and used as feature. Regarding to the synchronous classifier a Stepwise Linear Discriminant Analysis (SWLDA) was applied to data from the 6 Control runs in order to extract the 60 most significant control features. Also 6 cross-validation rounds were carried out using data from the 6 Control runs exploring all the possible combinations of 5 runs as training data set and 1 run as testing data set. Classification accuracy was then assessed as a function of the stimulation sequences accumulated in a trial in order to define the number of sequences to be used in the online session (see Online Performance section). SWLDA was applied to extract control features for the asynchronous classifier too, the only difference being that the 2 No-Control runs from the offline session were introduced in the training dataset. The thresholds values for the asynchronous classifier were defined through a procedure relying on the Receiving Operating Curves (ROCs) of score values [5]. In particular the thresholds values were chosen so that the false positive rate would not exceed the 5%.

C. Online Performance

The aim of the on-line session was to evaluate classification accuracy for both the synchronous and the asynchronous classifier. The number of stimulation sequences used for classification was not fixed for the asynchronous classifier, but it depends on how fast the threshold was reached by the score values accumulated in the trial. During the synchronous
**Control runs**, the number of stimulation sequences per trial was set equal to the lowest number that, in the off-line cross-validation, allowed reaching at least 95% accuracy. This choice aims to put the synchronous classifier in the most similar conditions with the asynchronous one. No error correction was required to the subject both for the synchronous and the asynchronous classifier, so that each run provided a total of 6 selections. With the asynchronous classifier abstentions could also occur; in this case subjects were required to try to select again the desired character. The control parameters for the synchronous *Control runs* were extracted from the 6 *Control runs* of the off-line session, these runs were also used with the two No-*Control runs* to extract control parameters and thresholds values for the asynchronous *Control* and No-*Control runs*.

### D. Efficiency evaluation

In order to evaluate synchronous and asynchronous systems efficiency we used the metric proposed by Bianchi et al. [6] doing some assumptions about the error cost: we associated a cost of 1 to the abstentions (the user only needs to repeat the trial trying to select again the desired character), while we associated a cost of 2 to misclassifications, because in this case the subject first has to delete the wrong character and then select again the desired one. The latter assumption is still valid if the desired symbol is misclassified with the UNDO item, so that a correct symbol is deleted.

### III. RESULTS

#### A. Online Performance

Figure 1a and 1b illustrate the results obtained during the *Control runs* with the synchronous and the asynchronous classifier respectively. On average, errors were higher for the synchronous system (12.04%) than for the asynchronous (7.11%). Despite the lower percentage of errors, the asynchronous system exhibited a lower percentage of correct classifications (74.66%) with respect to the synchronous (87.96%).

| Table I Efficiency values for the asynchronous and the synchronous system |
|-----------------|----------------|-----------|-----------|-----------|-----------|-----------|
| Subj1 | Subj2 | Subj3 | Subj4 | Subj5 | Subj6 |
| Async | 0.12 | 0.16 | 0.23 | 0.11 | 0.15 | 0.10 |
| Sync | 0.04 | 0.11 | 0.08 | 0.08 | 0.09 | 0.08 |
| Subj7 | Subj8 | Subj9 | Mean | Std |
| Async | 0.11 | 0.01 | 0.33 | 0.15 | 0.09 |
| Sync | 0.10 | 0.07 | 0.21 | 0.10 | 0.04 |

This was due to the high percentage of abstentions that occurred (18.23%). Every subject exceeded 60% correct classifications with the asynchronous classifier, except for subject 8 who exhibited more than 70% abstentions.

Table I provides efficiency values for the asynchronous and the synchronous classifier relaying on the on line results. As it can be seen the former exhibited a higher efficiency with respect to the latter and this difference resulted statistically significant from a Mann-Whitney U-test (p<.05).

#### IV. Conclusion

In this study, we described and evaluated a gaze independent P300-BCI system and a classifier able to output its decision after a variable number of stimulation sequences, or even to abstain, depending on the quality of the input signal. We compared the performance of the new classifier with the one of a classical synchronous classifier and the preliminary findings allowed to conclude that the former can significantly increase communication efficiency for gaze independent P300-based BCIs.

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#### REFERENCES