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Control or No-Control? Reducing the gap between Brain-Computer Interface and classical input devices

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Abstract— **In order to improve Brain Computer Interface usability for real life context, they should be able to adapt their speed to the user's current psychophysical state and to understand from the ongoing EEG when he/she intends to suspend the control. In this work we evaluated an asynchronous classifier which provides these feature with 20 healthy subjects, who were engaged in an environmental control task or in a spelling task. We also demonstrated how the proposed classifier can improve communication efficiency with respect to classical synchronous classifiers.**

I. Introduction

Brain Computer Interface systems aim to restore communication and interaction with the external world in people with severe motor impairments. Non-invasive BCI based on electroencephalographic (EEG) signals can detect voluntary modulations of cerebral activity or particular responses to external stimuli and translate them into a control signal for an external device[1]. The P300 event related potential (ERP) is widely used as control feature for BCI systems both for communication and environmental control[2], it is typically a large and positive deflection in the EEG activity which reaches a maximum of amplitude (ca. 10-20μV) over the centro-parietal scalp areas and occurs 250 to 400 ms after a relevant stimulus (Target stimulus) presented within a train of frequent stimuli (No-Target stimuli) is recognized [3]. Classical P300-based BCIs work in a synchronous mode: after a well defined number of stimulation the system always makes a "decision", assuming that the user is constantly attending to the stimulation. This mode of operation conditions works well in a laboratory context but it may have some limits for the use of BCI systems as assistive technology in real life context. In fact, to reduce the gap between BCI systems and classical input device (such as keyboard or mouse) they should be able to automatically suspend the control without the need for an explicit pause button when users divert their attention from the stimulation, and they also should be able to dynamically adapt their speed (the number of stimuli repetitions needed to achieve a classification) to the users' current state. This work presents the results of an asynchronous classifier trying to solve these problems. It was evaluated both for an environmental control task (database A) and for a spelling task (database B) in different operation conditions and global performance were compared to the performance of a classical synchronous P300-based BCI from the point of view of the communication efficiency.

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II. Methods

A. The asynchronous classifier

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. In particular the thresholds values were chosen so that the false positive rate would not exceed the 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 predefined number of repetitions of the stimuli, the system abstains from making a selection and a new trial begins (abstention). To make the system more robust to false positives when users are not engaged in controlling the interface, data acquired during a No-Control periods were added to the training data set[4][5].

B. Database A: environmental control

Eleven healthy volunteers (4 females, 7 males; mean age 26.4 +/- 4 years) were involved in this part of the study. The acquisition protocol was based on the P300 Speller interface [6] adapted to control a home automation system by using a 4 by 4 matrix containing 16 black and white icons representing the available actions on the environment. Stimulation and data acquisition was managed by the BCI2000 framework [7]. Stimuli consisted in the intensification of rows and columns of the matrix. Each stimulus was intensified for 125ms with an inter stimulus interval (ISI) of 125ms. Scalp EEG potentials were recorded (g.MobiLab, gTec, Austria, sampling rate 256 Hz) from 8 scalp positions (Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8). Each channel was referenced to the linked earlobes and grounded to the left mastoid. Here we indicate with the term *Sequence* a complete cycle of intensification of each row and column. Ten Sequences make a *Trial*. For each subject we acquired 4 Control *runs,* made of 8 Control trials, and 12 Alternate *runs* during which Control and No-Control trials alternated for a total of 10 trials per run. During the No-Control trials the subjects voluntarily diverted their attention from the stimulation performing three simple no control tasks:

- Fixation Cross, 30 trials: Subjects were instructed to fixate the cross in the centre of the interface and to ignore the stimulation;
- Watch & Listen, 15 trials: Subjects were instructed to watch a movie displayed on the half of the screen beside the matrix;
- Computation, 15 trials: Subjects had to answer simple arithmetic questions posed by the operator while fixating the cross.

Control runs were used to assess the accuracy of the Synchronous system, by repeating 6 rounds of 2-fold cross-validation. In each round, we used 16 trials to extract significant control features by Stepwise linear discriminant analysis (SWLDA [8]) and 16 trials as testing set. A similar procedure was also applied to the alternate runs, to evaluate the performance of the asynchronous system. In each round, the training dataset was composed of 35 Control trials, and 35 No-Control trials (15 Fixation, 10 Watch & Listen and 10 Computation), while the testing dataset was composed of the 25 remaining Control trials [4].

C. *Database B: copy spelling*

Nine healthy subjects (5 females, 4 males mean age = 26.4 ± 4.4) were enrolled in the study. All of them had previous experience with P300 based BCI and the GeoSpell interface[9]. The latter was designed to be operated in covert attention mode, so that it can be used also if ocular movements are impaired. In the GeoSpell interface the 36 alphanumeric characters of the Farwell and Donchin's Speller were redistributed on the vertices of 12 hexagons hereinafter defined as groups or stimulation classes. Each character belongs to two groups, in which it is displayed on the same vertex. A fixation cross was displayed in the center of the stimulation interface at all times. The distance between the fixation cross and each character was fixed so that the visual angle is lower than 1 degree. Stimulation consisted in the pseudo-random appearance of groups (stimulus duration 125ms and ISI of 125ms) and was provided by a modified version of the BCI2000 framework.
Scalp EEG signals were recorded from 8 positions (Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8; gUSBamp, gTec, Austria, sampling rate 256 Hz). Each subject 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, 10 stimulation sequences were delivered. Also each subject performed 2 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.

To assess performance of the synchronous classifier, a 6-fold cross-validation was carried out using data from the 6 Control runs. Classification accuracy was then assessed as a function of the sequences accumulated in a trial in order to define the number of sequences to be used to define system efficiency (see Efficiency section). Regarding the asynchronous classifier, a 6-fold cross-validation was also performed. In this case, the 2 No-Control runs from the off-line session were introduced in the training dataset and SWLDA was used to extract the control features.

D. *Efficiency*

In order to evaluate synchronous and asynchronous systems efficiencies, we used the metric proposed by Bianchi et al.[10]. This metric starts from the extended confusion matrix (ECM), which consists in a N by N+1 matrix, where N is the number of the available symbols. The additional column reports the number of cases in which the classifier abstains from taking a decision. To estimate the probability of incorrect or indeterminate classification of a symbol , a misclassification probability matrix (MPM) can be defined from the ECM. From the MPM, the extended overtime matrix (EOM) is built, representing the costs associated with errors and abstentions in terms of extra steps that have to be done to correct mistakes. The values for the MPM[i,i] correspond to the likelihood that the Target is correctly recognized, so the costs associated with errors for EOM[i,i]=0. We made assumptions about the misclassification cost, associating a cost of 1 to abstentions (the user only needs to repeat the trial), while we associated a cost of 2 to misclassifications (they can be corrected by selecting the respective UNDO actions and by selecting again the desired symbol). The latter assumption is still valid when the UNDO is unintentionally selected, thus deleting a correct symbol. The super tax vector (ST) is then defined as:

$$ST(i) = \sum_{j=1}^{N+1} MPM[i,j] \cdot EOM[i,j] \qquad (1)$$

Where i denotes the desired class and j indicates the predicted class. Considering all symbols on the matrix equally probable, we can define the expected selection cost ($\overline{ESC}$), which is the number of classification required to generate a correct logical symbol:

$$\overline{ESC} = \sum_{i=1}^{N} \frac{1}{1 - ST[i]} \qquad (2)$$

The Efficiency of a system, which takes into account the time needed to achieve a classification, expressed in number of stimulation sequence (NumSeq), will be:

$$Eff = \frac{1}{NumSeq * \overline{ESC}} \qquad (3)$$

For the asynchronous classifier the NumSeq corresponds to the mean number of sequences needed to exceed the thresholds. To put the synchronous classifier in the same conditions of the asynchronous one, we set the NumSeq for the synchronous classifier so that the accuracy assessed with offline crossvalidation reaches 95% (corresponding to the 5% of false positives admitted in the asynchronous classifier), up to a maximum of NumSeq = 10.

E. Robustness to false positives during No-Control periods

Each subject performed Online No-Control runs operated by the asynchronous classifier in order to assess system robustness to false positives when subject diverted their attention from the stimulation. Subjects participating to database A performed 2 online No-Control runs. Each Online No-Control run took 5 minutes during which the stimulation was kept on. During the first and second No-Control run, the subjects were asked to refrain from the control by watching a movie or by answering to arithmetic questions, respectively, while looking at the fixation cross. Subjects of database B were required to perform 2 online No-Control runs lasting 2 minutes and 30 seconds each and the tasks were the same of their 2 off line No-Control runs.

III. Results

A. Accuracy for the synchronous and the asynchronous classifier

Figure 1 shows the performance of both synchronous and asynchronous classifier. When a character or an icon was correctly recognized and selected it was defined as a "correct". If a classification occurred but the system selected an undesired character it was defined as an error, finally an abstention occurred when the threshold was not exceeded, and the latter was only possible for the asynchronous classifier.

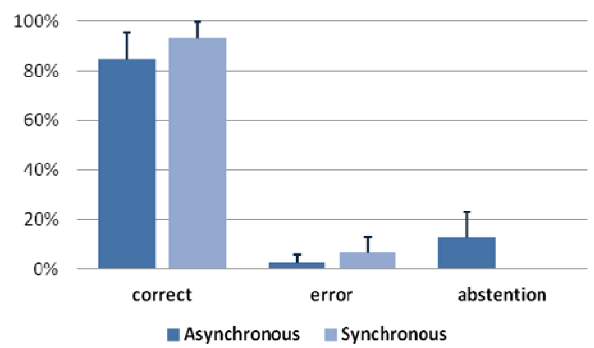

Fig. 1. Offline performance of the asynchronous and the synchronous classifier

We performed three 2-way ANOVA (CI=.95) considering the *paradigms* (environmental control/copy spelling) and the *classification mode* (asynchronous/synchronous) as factors and the *corrects*, the *errors*, and the *number of stimulation sequences* as dependent variables respectively. The synchronous classifier on average exhibited an higher percentage of correct classification with respect to the asynchronous one (93.27% ± 6.53 and 84.49% ± 11.27% respectively; F(1, 36)=9.7813, p=.00348), however the error rate was lower for the asynchronous classifier than for the synchronous one (2.85% ± 3.07 versus 6.73% ± 6.53; F(1, 36)=5,.431, p=.0294), since the former avoids errors through the abstentions (12.66% ± 10.48). Furthermore it should be considered that the number of sequences needed to achieve a classification was significantly lower for the asynchronous classifier (4.5 ± 1.06) than for the synchronous one (6.85 ± 2.56), as confirmed by the 2-way ANOVA (CI=.95) on the two distributions (F(1, 36)=13.870, p=.00067).

B. Efficiency

Table I reports the communication efficiency values for the asynchronous and the synchronous classifier for both the considered tasks. The asynchronous control exhibited a higher efficiency (0.21 ± 0.06) with respect to the synchronous classifier (0.17 ± 0.08). However this difference was not statistically significant as assessed by a 2-way ANOVA considering the *paradigms* (environmental control/copy spelling) and the *classification mode* (asynchronous/synchronous) as factors and the *Efficiency values* as dependent variables (F(1, 36)=3.4542, p=.07128). Considering the Information Transfer Rate (ITR) assessed by the Wolpaw's metric[11], which considers errors and abstentions in the same way, the asynchronous system exhibited an higher value (19,8 ± 9.19 bits/min) with respect to the synchronous classifier (17.3± 9.61 bits/min), but this difference was not significant as assessed by a 2-way ANOVA with *paradigms* and *classification mode* as factors and *ITR values* as dependent variables (F(1, 36)=.72306, p=.40076).

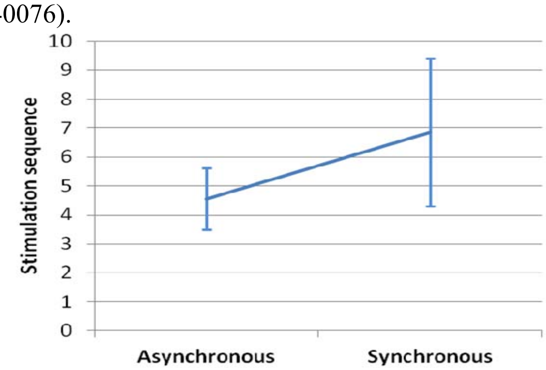

Fig. 2: mean value of the number of sequences needed to achieve a classification with both synchronous and asynchronous classifier

Table I: efficiency values for environmental control and copy spelling task

Environmental control			Copy spelling task		
	Asynch	*Synch*		*Asynch*	*Synch*
Subj1	0.27	0.20	**Subj12**	0.18	0.25
Subj2	0.14	0.07	**Subj13**	0.18	0.20
Subj3	0.32	0.32	**Subj14**	0.21	0.17
Subj4	0.23	0.19	**Subj15**	0.21	0.14
Subj5	0.27	0.18	**Subj16**	0.17	0.12
Subj6	0.20	0.32	**Subj17**	0.20	0.11
Subj7	0.29	0.24	**Subj18**	0.18	0.14
Subj8	0.13	0.08	**Subj19**	0.15	0.11
Subj9	0.16	0.05	**Subj20**	0.37	0.25
Subj10	0.16	0.08	**Mean**	**0.21**	**0.17**
Subj11	0.27	0.18	**std**	**0.06**	**0.08**

A. Robustness to false positives

During the Online No-Control runs on average 0.21 false positives/min were detected

IV. DISCUSSION

Understanding the user's intentions from the ongoing EEG such as when he/she wishes to suspend the control or when he/she recognizes an error represents an important issue which could improve usability and reliability of BCI system. To this aim, at the state of the art several classification algorithms have been proposed for P300 based BCIs[12][13][14]. However they only provides solution to dynamically adapt the number of stimuli repetitions and are not able to abstains from taking a decision if the user diverts his attention from the stimulation, or if the EEG signal is not reliable enough. While the statistical approach proposed in [15] provides this feature, it should be stressed that i) their test were carried out on a small number of subjects (4); ii) they reported a lower robustness to false positives during No-Control periods (0.71 false positives/min) and an Information Transfer Rate of 20 bits/min. Other asynchronous paradigms have been proposed based different control features, Panicker et al. [16] combined P300 potential with Steady state visual evoked potentials (SSVEPs) for the detection of the control state reporting an ITR of 19.05 bits/min during control periods and false alarm rate of 4.2% during No-Control periods. Diez et al.[17], with high frequency SSVEPs, reported an ITR varying from 9.4 to 45 bits/min. Zhang et al. [18] recently proposed an asynchronous paradigms based on the N200 speller and the motion visual evoked potentials (mVEPs). The latter paradigm allowed to reach during on line tests on 9 healthy subjects 70,1% accuracy during control periods, while 2,38 false positives/min were detected during No-Control periods. Considering user needs and requests [19] 0.21 false positives/min may still be considered unsatisfactory for a continuous use. However this value may be acceptable for short pauses such as waiting for an answer during a talk, or thinking about what we are going to write. From the other side, abstentions may also occur during a control period, thus reducing the system's accuracy with respect to a classic synchronous classifier. As we demonstrated in the current work, considering that error recovery have a higher cost than abstentions, the asynchronous system exhibits a higher communication efficiency because of its lower error rate with respect to the synchronous classifier.

V. CONCLUSIONS

In this work we evaluated the efficiency of an asynchronous P300-based BCI assigning different cost to errors and to unwanted misclassifications. Particularly, we analyzed data from two different databases, related to i) environmental control and ii) copy spelling task in covert attention conditions. Although the synchronous classifier exhibited a higher percentage of correct classifications with respect to the asynchronous one, taking into account the lower misclassification cost for abstentions than for errors, we demonstrated that the asynchronous system is more efficient than a synchronous system in terms of time needed to achieve a selection, stressing the advantages of the former with respect to the latter. Finally the asynchronous system revealed an acceptable robustness to false positives when the subject is not attending to the stimulation.

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