TOWARD DOMOTIC APPLIANCES CONTROL THROUGH A SELF-PACED P300-BASED BCI

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Abstract: During recent years there has been a growing interest in Brain Computer Interface (BCI) systems as an alternative means of interaction with the external world for people with severe motor disabilities. The use of the P300 event-related potentials as control feature allows users to choose between various options (letters or icons) requiring a very short calibration phase. The aim of this work is to improve performances and flexibility of P300 based BCIs. An efficient BCI system should be able to understand user's intentions from the ongoing EEG, abstaining from doing a selection when the user is engaged in a different activity, and changing its speed of selection depending on current user's attention level. Our self-paced system addresses all these issues representing an important step beyond the classical synchronous P300 BCI that forces the user in a continuous control task. Experimentation has been performed on 10 healthy volunteers acting on a BCI-controlled domestic environment in order to demonstrate the potential usability of BCI systems in everyday life. Results show that the self-paced BCI increases information transfer rate with respect to the synchronous one, being very robust, at the same time, in avoiding false negatives when the user is not engaged in a control task.

1 INTRODUCTION

A BCI system allows to control simple devices, including communication facilities, without using muscles and peripheral nerves (Wolpaw et al. 2002); in particular an EEG based BCI system is able to understand user's intentions translating his brain activity into a control signal (Wolpaw and McFarland, 2004). Progresses made in recent years have brought these systems to be considered as an alternative means of communication and control in situations where environmental conditions can transiently compromise the mobility of the user, and not only for people with severe disabilities. The P300 event-related potential is typically a large and positive deflection in the EEG activity (ca. 10-20μV) with a latency ranging between 250 and 400 ms (Polich et al. 1995, Fabiani et al.1987). It is elicited when the subject recognizes a particular stimulus (Target stimulus) presented within a train of frequent stimuli (NoTarget stimuli). An average of several epochs related to a specific target stimulus is required to distinguish the P300 potential from the spontaneous EEG activity. For this reason classic P300 based BCI systems provide a well-defined number of stimulation repetition at the end of which a selection is made; this last issue is the cause of obvious drawbacks because the user is continuously engaged in controlling the interface and his distractions produce wrong classifications. Moreover, the number of stimuli repetitions needed to make a selection (and therefore time) depends on the user's attention level; few sequences are needed if the user is very concentrated, but fatigue or distractions may cause a significant decrease in performance and in this case it is preferable that the system refrains from making selections avoiding a wrong classification. This work presents a methodology for the classification of EEG signals related to P300 potentials which allows the user to divert attention from the stimulation interface, suspending the control, without incurring in a wrong

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classification (selection). In order for the BCI systems to move from research labs to people's homes it is absolutely necessary that they are able to recognize user's state without any outside input; in particular they have to detect user's control state or, in other words, to distinguish when the user intends to operate through a control interface from when he is engaged in a different task and therefore to avoid making any selections. This is why in recent years many research groups have been involved in the problem of a self-paced BCI, both for the motor imagery (Mason and Birch, 2000; Millan and Mourino, 2003; Townsend et al, 2004) and for the P300-based systems (Zhang et al, 2008).

In this work we show a simple and fast self-paced system based on an heuristic method; we allow the system to recognize user's status, introducing thresholds in the classifier. Moreover the choice of Target stimulus become dynamic and this allows system to improve its selection speed depending on the user's ability and attention level. For this reason particular attention will be also put on system performances in terms of information transfer rate (ITR) and accuracy. Another important thing to emphasize is that we conducted our experiments in an environment completely operated by the BCI system (Cincotti et al. 2008) and we based user's task on real life situations. This is because we want to demonstrate the feasibility of using these systems in everyday life.

2 MATERIALS AND METHODS

For the aim of acquisition protocol we investigated the use of P3Speller application (Farwell and Donchin, 1988) provided with the BCI2000 framework (Schalk et al. , 2004) to control an home automation system. We organized 8 different stimulus classes in a 4 by 4 matrix, each consisting of a row or a column.

Matrix elements were 16 simple B&W icons (in order to minimize the variability and possible VEPs due to a high variety of colors and load information of each icon) representing the actions that the user could perform on the environment (e.g. light control, DVD player, webcam for remote monitoring, mobile phone and opening the door). Stimulation consisted in a random intensifications of each stimulus class, with a duration of 125ms each one. Inter Stimulus Interval (ISI) was set to 125ms, so 250ms lag between two stimuli.

We distinguished two different states in which the user can be: the Control State, during which he/she was attending to the stimulation because he intended to exercise control over the surroundings through the interface; and the NoControl State, during which the user was engaged in another task and then he wanted the system refrained to make decisions. The EEG signal was reorganized in overlapping epochs representing the 800 ms time intervals immediately following the onset of each stimulus; we can distinguish the epochs acquired during Control trials in Target Epochs and NoTarget Epochs. Target Epochs relate to the onset of the row or the column stimulus containing the icon that the user intends to select, while NoTarget are related to no relevant stimuli. Then epochs were grouped into sequences; a sequence denotes a single presentation of each stimulus class on the control interface; in this case a sequence consisted of 8 epochs, one for each stimulus class of the interface. A single sequence lasted 2 seconds. With the term Trial we refer to a set of sequences at the end of which a selection is made. Between 2 Trials we took 4 seconds during which the system presented to the users the Target icon. All the icons on the interface were proposed as a Target to the subject with the same frequency and this because we wanted that each stimulus was equally likely for subsequent analysis. Finally, a Run consists of a series of trials at the end of which data acquisition is stopped.

2.1 Data Acquisition Protocol

10 volunteers participated to data acquisition protocol (4 female and 6 male) aged between 23 and 38 years; 5 subjects had already experience with the BCI systems. Scalp EEG data were acquired from each subject during BCI sessions using the g.MobiLab device from g.Tec (Austria, 256Hz). The EEG was recorded from 8 Ag-AgCl electrodes : Fz, Cz, Pz, Oz, P3, P4, PO7 and PO8. This channel set represents the union of the classical channels used to extract the P300 response (Fz, Cz and Pz) with channels in the posterior regions that have strong correlation with desired matrix target (Krusienski et al. 2006).

Each subject completed 2 recording sessions, we used collected data for subsequent off-line analysis and during recording session subject had not any feedback about classification results. The first recording session included a total of 8 runs, the first 2 compounded of 8 trials each during which the subject was asked to always exercise control on the interface; the number of stimulation sequences per trial was fixed a priori to 10. Over the last 6 runs Control Trials and NoControl Trials were alternated for 10 trials in total. During the NoControl Trials the subject was asked to focus the eyes on a fixation cross in the center of the stimulation interface. This is because we wanted that the subject was not completely immune to the stimulation even when he was in the NoControl state. It is assumed that a BCI user can't move his head or eyes to ignore the stimulation, so it is essential that the NoControl state is robust to random stimuli which the user does not actually paying attention to.

The second session provided 2 runs in Control State to verify the subject's attitude to control the interface using the P300 potential, and 6 runs in which Control trials and NoControl trials were alternated, however we considered different NoControl tasks; in fact, the last 6 runs can be divided into 2 groups of 3 runs each:

- Control and View: The subject during the NoControl Trials was watching a video on the other half of the screen.
- Control and Answer: During the NoControl trials the subject had to do computation as quickly as possible looking at the fixation cross at the center of the interface.

Following this approach the data set contains NoControl trials representing real situations in which the user turns his attention elsewhere or speaks with another person.

2.2 Features Extraction and Classification

Signal preprocessing is necessary before perform the classification. In particular, the EEG signal was divided into overlapped epochs of 800 ms starting from the onset of each stimulus, and then each epoch was down-sampled at 85 Hz. Such down-sampling reduces the data size and at the same time speeds up the ensuing EEG processing significantly. Then, EEG epochs were reorganized into a three-dimensional array: each 2D matrix of the array represents a single epoch related to a single stimulus, where rows represent acquisition channels and columns correspond to samples of each epoch.

Despite this first preprocessing the amount of data was still significant and a further reduction in features space was performed using the Stepwise Linear Discriminant analysis (SWLDA). Stepwise Linear Discriminant analysis (Draper and Smith, 1981) is an extension of Fisher's linear discriminant (FLD, Fisher 1936) that performs feature space reduction by selecting suitable features to be included in the discriminant function. Farwell and Donchin first introduced this method for classifying P300 features into EEG signal (Farwell and Donchin, 1988); Krusienski et al. confirmed that this simple technique is really efficient for online communication (Krusienski et al., 2008). We ran the stepwise function on a testing data set including NoControl trials. We assigned a label equal to zero to the NoTarget and NoControl epochs while label was equal to 1 for Target epochs. Using SWLDA, the final discriminant function was restricted to contain a maximum of 60 features. Nonzero weights were assigned to these features, *w*. Then the scores values for each epoch were calculated as:

$$y_j = \sum_i w \cdot f_i + b \qquad (1)$$

Where i denote all features related to single stimulus j. It is assumed that a P300 is elicited for one of the four row/column intensifications during Control trials, and that the P300 response is invariant to row/column stimuli, the resultant classification is taken as the maximum of the scored feature vectors for the respective rows, as well as for the columns:

$$predicted\ row = arg \max_{row} y_{row}$$

$$predicted\ coloum = arg \max_{col} y_{col}$$

The icon that appears at the intersection of the predicted row and column in the matrix is the one chosen.

$$predicted\ icon = predicted\ row \bigcap predicted\ column$$

2.3 Threshold Values

Self-paced control is based on the introduction of some thresholds in the classifier; the classification was performed as explained before but the system will refrain from making a selection until a row and a column scores exceeds the threshold value. The threshold values were chosen through a procedure that relies on the use of ROC curves. In particular we calculated the scores value on the Target, NoTarget and NoControl epochs. A normal distribution well fit the scores distributions and to confirm this we ran a t-test on the 3 different score distributions for each subject. T-test results show that the hypothesis of normal distribution is true with 95% confidence level. Next step was investigating if the 3 score's distributions can be considered different; for this reason we ran the Kolmogorov-Smirnov test on each pair of samples. Table 1 report the results of this test; the hypothesis of different distribution was confirmed with the 95%

confidence level for all subjects except one (Subject 1: No Target vs NoControl). For this reason it is necessary to take account of NoControl trials for thresholds extraction.

Table 1: Kolmogorov-Smirnov test on each pair of sample.

	Target vs NoTarget	*Target vs NoControl*	*NoTarget vs NoControl*
SUBJ 1	8,75E-192	9,65E-196	0,44287182
SUBJ 2	1,74E-154	1,84E-136	6,99E-04
SUBJ 3	8,52E-256	6,38E-205	2,01E-21
SUBJ 4	2,74E-213	1,79E-182	2,82E-11
SUBJ 5	1,24E-198	3,95E-159	2,48E-10
SUBJ 6	1,81E-255	3,42E-207	9,35E-19
SUBJ 7	1,77E-277	2,77E-241	2,67E-23
SUBJ 8	2,34E-177	4,52E-134	8,90E-22
SUBJ 9	1,04E-147	2,30E-107	2,39E-13
SUBJ 10	6,67E-178	1,14E-126	1,31E-24

The threshold values were chosen according to the number of stimulation sequences accumulated in the trial. In fact the scores for the general stimulus *i* at the sequence *s* will be defined as:

$$yacc_i^s = yacc_i^{s-1} + y_i^s \quad s = 1,2,\dots NumSeq$$
$$i = 1,2,\dots Ns \qquad (2)$$

Where y_i^s is given by (1), Ns = 8 for the domotic interface and the number of stimulation sequences was fixed to 10.

Subsequently, for each sequence we looked for the maximum score of the row stimuli and the maximum score of the column stimuli, and then to them was assigned a label equal to 1 if the maximum scores were relative to a Target stimulus and equal to 0 if it referred to NoTarget or NoControl stimuli. In this way we are sure to include the maximum score values related to NoControl trial in ROC curves training, so threshold values taking into account possible artifacts that may occur when the subject was not engaged in BCI control. Now ROC curves can be plotted for each sequence using the corresponding scores. An example is shown in figure 1 where it is evident that when the number of sequences accumulated in the trial increases the ROC curves assume an ideal trend. Finding a tradeoff between false positive rate and false negative rate, is necessary in order to choose the threshold. We have chosen to set the maximum False Positive Rate (FPR) to 0.05 and the lowest True Positive Rate (TPR) to 0.5, so the threshold will be chosen at the intersection of the ROC curve to the straight line joining points (0.1) and (0.05 and 0.5) .

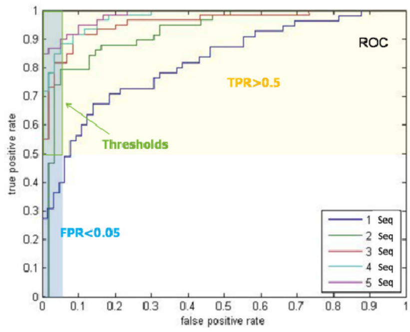

Figure 1: Area under the ROC curve: thresholds are identified from a tradeoff between the True Positive Rate (yellow area) and False Positive Rate(blue area). Figure shows only the first five stimulation sequences, over the trend is approximately the same.

3 RESULTS

This section describes the results obtained through the off-line analysis performed on data acquired during the 2 recording sessions. Then we compare our self-paced system with a classic P300 based BCI in terms of information transfer rate considering only the Control trials.

3.1 Off-line Analysis

An off-line cross validation was performed on the data collected during recording sessions. In particular, we divided the data into a training data set consisting of 3 runs from the first session and 4 runs from the second session. In this way we included in the training data set NoControl trials related to all 3 different NoControl tasks. The remainder of the data set was used as a test data set. Specifically, the train data set was used for features extraction and to select the threshold values. The figure 2 shows the results obtained in cross validation.

There are 5 different classification outcomes, depending on the user's state.

During Control trials we can distinguish between:

- Correct Classification: the target is correctly recognized;
- Wrong Classification: there's a target misclassification;
- Missed Classification: the thresholds are never exceeded, for this reason the system abstains from take a decision.

During NoControl trials possible classification outcome can be:

- Abstention: the system properly refrain from taking decisions;
- Missed Abstention: the thresholds are exceeded and the system wrongly makes a choice.

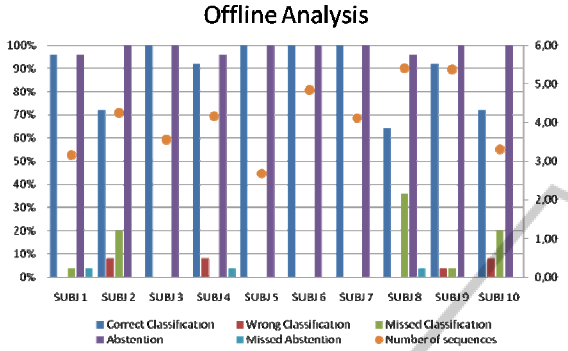

Figure 2: Results of offline cross validation for Control and No-Control task.

Figure 2 also shows the averaged number of sequences needed to make a selection when the user was in the Control state. From the graph it can be see how the system was proved to be robust during NoControl trials in fact Abstentions reached an average of 98%. On the other hand there is a high percentage of abstentions during the Control trials (average 8,4%), this may seem an inconvenience but it really represents the system's ability to avoid misclassification, because the percentage of wrong classification did not exceed an average of less than 3%. We used the first 2 runs of the first 2 sessions, in which the subject was always in a Control state, to assess his ability with a classic P300-based BCI. We found the ‘optimal' number of stimulation sequences just doing a cross validation offline: particularly we used 2 runs to train SWLDA and to extract significant features and the other 2 to test these parameters, then we averaged the results of classification for each possible combination of training and testing data set. The figure 3 shows the trend of the percentages of correct classification based on the number of stimulation sequences accumulated for each subject. The black line represents an accuracy of 95%, which corresponds to a false positive rate of 5% that is the maximum of false positive allowed in the self-paced system through ROC curves. We used these results to estimate the information transfer rate.

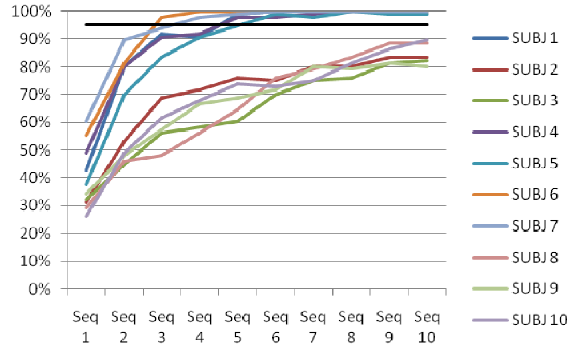

Figure 3: Results of offline cross validation for Control task depending on number of stimulation sequences.

3.2 Information Transfer Rate (ITR)

To assess the efficiency of the two systems in terms of information transfer rate we used the definition of bit rate given by Wolpaw et al.(2000) and widely used in BCI systems, this is based on the definition of information rate proposed by Shannon for noisy channels with some simplifying assumptions: the symbols have all the same a priori occurrence probability $p = 1/N_s$, the classifier accuracy P is the same for all target symbols and that the classification error $1 - P$ is equally distributed amongst all remaining symbols.

$$B_{Wolpaw} = \log_2 N_s + P \log_2 P + (1-P) \log_2 \left[\frac{(1-P)}{N_s - 1} \right] \quad (3)$$

This express the bit rate or bit/trial for each selection. The information transfer rate (bits/minute) is equal to B_{Wolpaw} multiplied by speed of selection S (Selection per minute). In turn the speed selection for P300-based system depends on the number of sequences of stimulation used and when we calculated it we have taken account of the 4 seconds between a trial and the other which are used to present the results of the classification. The Table 2 shows the values of ITR for each subject calculated using the average number of sequences and the percentage of accuracy obtained by off-line analysis both for self-paced BCI and for the synchronous one. In particular, for the synchronous system we imposed the number of stimulation sequences that allowed subject to achieve 95% of accuracy, if this did not happen we have used the minimum number of sequences that produced the highest accuracy.

Table 2: ITR in both modalities.

	SYNC	*SELF*
SUBJ 1	12,39	4,24
SUBJ 2	5,08	11,37
SUBJ 3	16,81	16,36
SUBJ 4	12,01	11,87
SUBJ 5	11,03	18,00
SUBJ 6	16,81	15,00
SUBJ 7	14,01	16,06
SUBJ 8	5,98	15,38
SUBJ 9	4,67	10,17
SUBJ 10	5,63	11,83
Mean	10,44	13,03

4 CONCLUSIONS

The introduction of a threshold based classification system in the P300-based BCIs allows the user to divert his attention from control interface at any time and without the use of external inputs, and it also brings positive effects on the bit rate that is incremented when the user is in the best control conditions. A further advantage consists in increasing the accuracy of the system by preventing errors through abstentions; in this way the BCI system acquires more dynamicity and flexibility by reducing its gap with traditional input interfaces. Future applications could consider the use of dynamic thresholds fitting the user's current action or the environment state: the system would be able to automatically identify the user's most likely action and facilitate its selection by reducing the threshold values for that item. This work represents a step towards the use of the BCI systems as an aid for functional communication and environmental control for people with severe motor disabilities or as alternative means when the usual channels of communication and interaction are temporarily compromised.

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