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GIBS Block Speller: Toward a Gaze-Independent P300-based BCI

Gabriel Pires, Urbano Nunes and Miguel Castelo-Branco

Abstract— **Brain-computer interface (BCI) opens a new communication channel for individuals with severe motor disorders. In P300-based BCIs, gazing the target event plays an important role in the BCI performance. Individuals who have their eye movements affected may lose the ability to gaze targets that are in the visual periphery. This paper presents a novel P300-based paradigm called gaze independent block speller (GIBS), and compares its performance with that of the standard row-column (RC) speller. GIBS paradigm requires extra selections of blocks of letters. The online experiments made with able-bodied participants show that the users can effectively control GIBS without moving the eyes (covert attention), while this task is not possible with RC speller. Furthermore, with overt attention, the results show that the improved classification accuracy of GIBS over RC speller compensates the extra selections, thereby achieving similar practical bit rates.**

I. INTRODUCTION

A brain-computer interface (BCI) directly translates brain signals into messages or commands, without recurring to output channels of peripheral nerves and muscles [1]. BCIs based on electroencephalographic (EEG) signals recorded on the scalp may provide a new communication channel for people suffering from severe motor impairments. P300 is an event related potential (ERP) modulated by attention that has been used worldwide to control BCIs. The first BCI system based on the P300 component was introduced by Farwell and Donchin [2]. The system, known as row-column (RC) speller, consists of a 6×6 matrix, where rows and columns are randomly intensified (flashed) according to an oddball paradigm. Target events (rare events) elicit a P300 component associated with the row or column that includes a symbol mentally selected. The RC paradigm has already shown successful results in clinical applications [3] [4]. Despite the successful results, the RC speller presents some aspects that limit its performance, such as: the frequent occurrence of adjacency-distraction errors, the double-flash errors, the overlapping of successive targets, the low target probability (1:6), and the strong influence of non-target flashes [5], [4]. Moreover, a high number of symbols/events of a paradigm may increase the number of distractors, which makes difficult the perception/discrimination of the flashing events. All these issues adversely affect the evoked P300 and its detection. In order to overcome some of these limitations, several approaches have been researched, proposing modifications to the RC speller or proposing alternative paradigms, e.g., see [5], [6], [7]. Another limitation of the RC speller is that it depends on eye gaze, i.e., subjects have to gaze the mentally selected letter. This issue, that has been addressed in [8], [9], [10], is particularly relevant for individuals that lose the ability to move the eyes (e.g. advanced stages of disorders such as amyotrophic lateral sclerosis). Detection with covert attention, i.e., without moving the eyes, is very difficult if targets are in the visual periphery since spatial acuity decreases with increased visual eccentricity, and because the identification of symbols is hampered by the crowded effect [8]. As a result, it is very difficult to attend the letters in the periphery of the RC matrix. To address this problem, several solutions have been proposed in [8], [11], [9] wherein the letters are placed at the center of the screen. However, in [8] and [11], the paradigms were not tested online. In [9], successful online results are presented but only for 10 repetitions of the same event.

In this paper we propose a new speller paradigm henceforth designated by GIBS (gaze independent block speller). This paradigm addresses the problem of covert detection. We show that GIBS allows the selection of the letters using covert attention and with effective transfer rates. On the other hand, we show that in overt attention experiments, the achieved classification rates of GIBS are superior to the ones achieved with RC speller. The paradigms are assessed online based on accuracy, number of repetitions and practical bit rates in bit per min (bpm).

II. METHODS

A. GIBS paradigm and RC speller

Screenshots of the proposed Block-speller are presented in Fig. 1 a) and b). The paradigm allows to select all letters of the alphabet, the symbols 0 and 1, the space ('sp'), and the delete ('dl'), totalizing 30 symbols. The symbols are grouped into four blocks following an alphabetical order. The symbols 'sp' and 'dl' are repeated in every group. The paradigm layout is composed by a group of 9 symbols in the center and 3 lateral small blocks with the remaining symbols. To select a symbol, the user has first to select the small block where it belongs. When the respective block is selected, the symbols of that block move to the center and the respective small block disappears (see Fig. 1 a) and b)). The user can then select the attended symbol. The symbols at the center are large, well apart, and placed in the visual angle of the fovea. The symbols at the center flash individually while the

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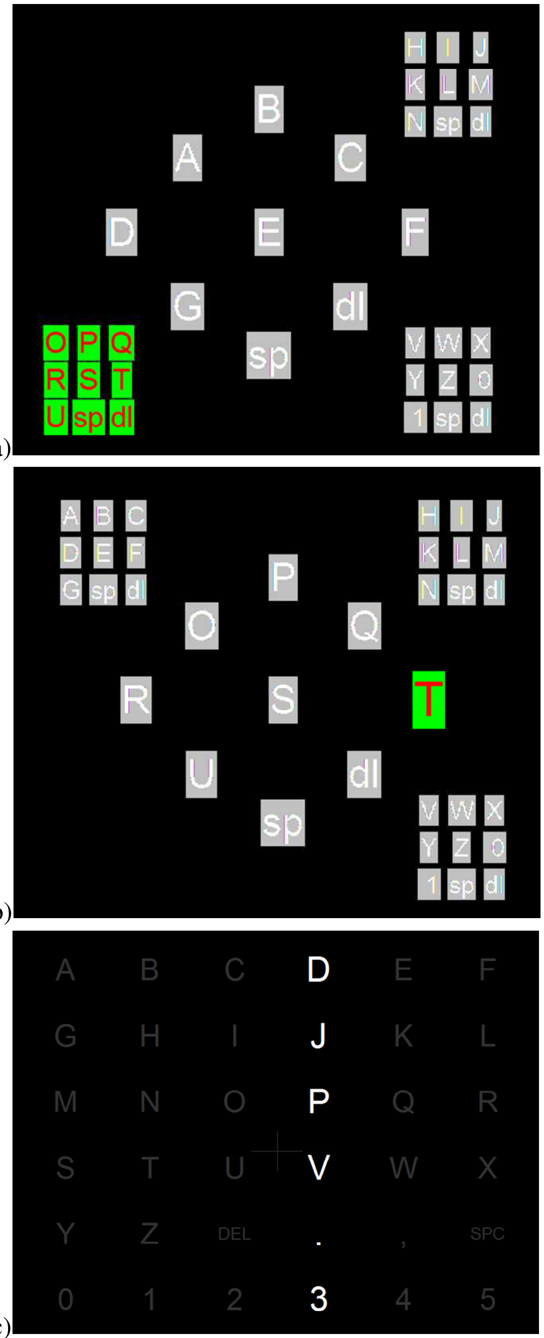
Gabriel Pires is with the Institute for Systems and Robotics, University of Coimbra, 3000 Coimbra, Portugal and also with the Department of Electrical Engineering, Polytechnic Institute of Tomar, 2300 Tomar, Portugal, and acknowledges a PROTEC research fellowship under Grant SFRH/BD/49881/2009. gpires@isr.uc.pt

Urbano Nunes is with the Institute for Systems and Robotics, University of Coimbra, 3000 Coimbra, Portugal urbano@isr.uc.pt

Miguel Castelo-Branco is with the Biomedical Institute for Research in Light and Image (IBILI), University of Coimbra, Portugal mcbranco@ibili.uc.pt



a)
b)
c)

Fig. 1. a) Screenshot of GIBS when a block is flashed; b) Screenshot of GIBS after the lower left block has been selected; c) Screenshot of the RC speller.

symbols within the small blocks flash as an entire block. The small blocks are placed outside of the visual fovea, but this does not represent a problem because the user has only to detect the entire block and not an individual symbol within the block. Since there are 9 symbols at the center and 3 small blocks flashing, the number of events is 12, and thereby the target event probability is 1:12. The symbol ’sp’ is used to separate the words of the sentences. Since this symbol is frequently used, it was included in all groups to enable its selection without having to switch between blocks. The ’dl’ symbol is also included in all groups with the same purpose. The stimulus onset asynchrony (SOA), i.e., the interval between the onset of two consecutive stimuli, was set to 150 ms, and the duration of each flash was set to 75 ms. The time between selections, i.e., the inter-trial interval (ITI) was set to 3.5 s.

From an information transfer rate perspective, the time taken for the transitions between blocks is clearly a disadvantage over the RC speller. However, GIBS has a lower target probability, a lower occurrence of double-flash, a lower probability of overlapping, and fewer elements of distraction when compared with RC. It is therefore expected that the P300 component elicited by GIBS will have a higher signal-to-noise ratio (SNR), leading thereby to an increased classification accuracy. An analysis of how much the classification accuracy should be improved to compensate the transitions between blocks is made in sections II-B and II-C.

The RC speller is based on the paradigm introduced in [2] as seen in Fig. 1c). The SOA and ITI were respectively set to 200 ms and 3.5 s.

B. Block transitions rate

To estimate the time required for a symbol selection in GIBS, we need first to estimate the average rate of transitions between blocks (N_{tr}). Taking several hundred of sentences of informal dialogs and generic texts in the English language we computed the average number of transitions that would occur using the groups of letters in Fig 1, i.e., using the alphabetical order {Group 1 = [’A”B”C”D”E”F”G’], Group 2 = [’H”I”J”K”L”M”N’], Group 3 = [’O”P”Q”R”S”T”U’], Group 4 = [’V”W”X”Y”Z”0”1’]}. The average number of transitions was $N_{tr} \approx 0.60$ transitions per selection. The possibility of reducing N_{tr} by using different groups of letters was also investigated. The average number of transitions was computed grouping the letters according to letters frequency and digrams frequency in the English language. The achieved number of transitions were respectively 0.51 for {Group 1 = [’A”E”I”O”N”S”T’], Group 2 = [’C”D”H”L”M”R”U’], Group 3 = [’B”F”G”P”V”W”Y’], Group 4 = [’J”K”Q”X”Z”0”1’]}, and 0.48 for {Group 1 = [’E”H”I”N”A”R”T’], Group 2 = [’O”B”C”M”P”S”U’], Group 3 = [’J”K”Q”V”W”X”Z’], Group 4 = [’D”F”G”L”Y”0”1’]}. So, it is possible to improve the N_{tr}, however these groups are less intuitive than the ones in alphabetical order and users may experience difficulty in memorizing the letters included within each group.

C. Bit rate metrics

In [1], Wolpaw *et. al* presented a metric to compute the information transfer rate (ITR) of a BCI system. The ITR formula was derived from Shannon’s theory [12], modeling the BCI system as a noisy communication channel (see Fig. 2). The average mutual information, $I(X;Y)$, between the intention of the user and the detection made by the BCI system is given by

$$I(X;Y) = H(X) - H(X|Y) \tag{1}$$

where $H(X)$ is the source entropy and $H(Y|X)$ is the information lost in the noisy channel, i.e., it represents the classification error rate of the BCI system. Assuming a BCI with N_s possible choices (number of symbols) which are equiprobable, and an online classification accuracy of P_{ac}, then $I(X;Y) \equiv B$, measured in bits/symbol, is given by

$$B = \log_2(N_s) + P_{ac}\log_2(P_{ac}) + (1-P_{ac})\log_2\frac{(1-P_{ac})}{(N_s-1)}. \tag{2}$$

Taking the rate of possible selections per minute r_s (symbols/min), then the ITR is expressed by

$$ITR = r_s B. \tag{3}$$

This formula has been widely used by the BCI community as a benchmark metric for performance comparison, particularly in P300-based BCIs. However, the use of this metric for the assessment of a BCI should always be accompanied with the accuracy [6]. Metric (3) can be fallacious because low levels of accuracy may provide reasonable bit rates and at the same time be unacceptable for communication. Several authors [5], [13] argue that a more practical and generic metric is needed to assess and compare BCIs. In P300 spellers, a metric that takes into account the correction of misspelled letters is more suitable because it clearly expresses the effect of classification accuracy. The time needed to correctly spell a letter can be obtained by computing the average number of retries, N_r. Each time an error occurs two additional selections are required (one for deleting and one for re-spell). The N_r value is computed according to [5], [13]

$$N_r = \frac{1}{1-2(1-P_{ac})} \tag{4}$$

which holds for $(1-P_{ac}) < 0.5$. The practical bit rate (PBR) is obtained from

$$PBR = \frac{r_s}{N_r}\log_2 N_s, \tag{5}$$

where $\log_2 N_s$ is the source entropy, $H(X)$. In our study, GIBS and RC speller are compared using this practical bit rate.

We know that for the same number of repetitions and classification accuracy, the bit rate for GIBS is lower than for the RC speller. Our goal now is to determine what should be the relative improvement in the classification accuracy of GIBS needed to compensate the time taken for transitions between blocks. The number of selections per minute is given

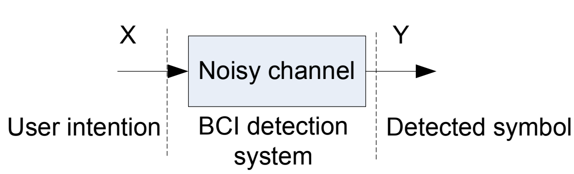


Fig. 2. BCI system modeled as a communication channel.

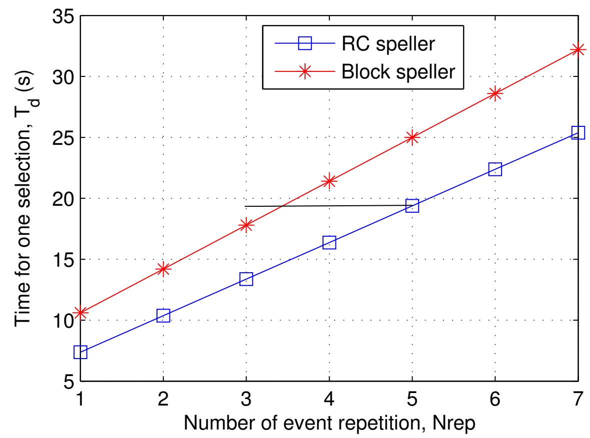


Fig. 3. Time duration of a trial (T_d) for RC speller (6) and GIBS (7) varying the number of repetitions and setting the classification accuracy to 90%.

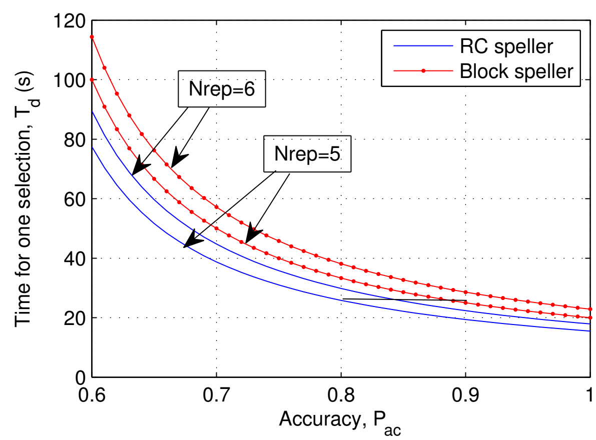


Fig. 4. Time duration of a trial (T_d) for RC speller (6) and GIBS (7) varying the classification accuracy and setting the number of repetitions to 5 and 6.

by $r_s = 60/T_d$, where T_d is the trial duration (time required for selecting a symbol). For the RC speller, the trial duration is given by

$$T_d = N_r(N_{rep} \times (N_{ev} \times SOA) + ITI) \tag{6}$$

and for GIBS, by

$$T_d = (1+N_{tr})N_r(N_{rep} \times (N_{ev} \times SOA) + ITI), \tag{7}$$

where N_{ev} is the number of events and N_{rep} is the number repetitions to make a symbol selection (N_{ev} is 12 for both paradigms and the number of transitions in GIBS is $N_{tr} = 0.60$). The difference of the values of T_d between the two paradigms depends simultaneously on the number of repetitions and on the accuracy. Taking (6) and (7), T_d for two different situations was analyzed. In Fig. 3, the classification accuracy was set to 90% for both paradigms, and the number of repetitions within a trial was varied. In Fig. 4, the number of repetitions was set to 5 and 6, while varying the classification accuracy. Some particular cases are presented to exemplify the analysis. In Fig. 3, we can see for example that it is possible to achieve a similar T_d by taking 5 repetitions in RC, and 3 repetitions in GIBS (illustrated in Fig. 3 by the horizontal line segment). In this particular case, to have the same T_d, the detection with GIBS would have to be achieved with two repetitions less than with the RC speller. Setting the number of repetitions and varying the accuracy, the curves in Fig. 4 show that, for example, for $N_{rep} = 5$, for an 80% accuracy in RC, a 90% accuracy is required in GIBS to achieve the same T_d, i.e., 10% more (illustrated in Fig. 4 by the horizontal line segment).

D. Participants and data acquisition

Four able-bodied subjects participated in this study of whom two were first time BCI users (S01 and S03). The EEG activity was acquired with a g.tec gUSBamp amplifier. Signals were recorded from 12 Ag/Cl electrodes at positions Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz and Oz of the international extended 10-20 standard system with a g.tec cap. Channels were selected according to our previous study [4]. Vertical and horizontal EOGs were also recorded to monitor movements of the eyes. The electrodes were referenced to the right or the left ear lobe and the ground was placed at AFz. Signals were sampled at 256 Hz, and filtered by a 0.1-30 Hz bandpass filter and a 50 Hz notch filter. The electrodes impedance varied from subject to subject, but were almost always kept under $10K\Omega$.

III. Experimental tests

A. Procedure

During the experiments, the participants were seated in front of a computer screen at about 60 cm. The experimental conditions for RC and GIBS paradigms were the same. Participants were instructed to be relaxed and to attend the desired target, mentally counting the number of intensifications of target events. Two different experiments were performed. In one experiment, the participants were allowed to gaze the target symbols (overt attention) and in the second experiment they were not allowed to gaze the target symbols (covert attention). In the second experiment, the HEOG and the VEOG signals were recorded to ensure that no ocular movements occurred. The online sessions were preceded by a calibration session of approximately 5 min. During the RC calibration phase, the user had to attend the letters of the word 'INTERFACE', and during GIBS calibration, the user had to attend 7 letters of the central group and 5 choices of small blocks. The labeled datasets obtained from calibration have 180 target epochs and 900 non-target epochs for the RC speller, and 96 target epochs and 1056 non-target epochs for GIBS. These datasets were used to obtain the models for online classification. The classification algorithms use the same methodology that was used in our previous work, which showed state of the art results with the RC speller [4]. It is based on a statistical spatial filter that is a cascade of a Fisher beamformer and a Max-SNR beamformer (C-FMS). The twelve EEG channels are transformed into two high SNR projections, which are then feed to a naïve Bayes classifier.

TABLE I
Online results - Overt attention.

Subject	Nrep	RC speller P_{ac}(%)	RC speller PBR (bpm)	GIBS P_{ac} (%)	GIBS PBR (bpm)
S01	5	100	20.01	-	-
	3	68.4	10.68	100	19.64
	2	-	-	78.9	14.25
S02	5	78.9	11.58	100	13.98
	3	-	-	94.7	17.57
S03	5	78.9	11.58	100	13.98
S04	5	89.4	15.79	100	13.98
	4	84.2	16.20	-	-
	3	-	-	89.4	15.50
Average	4.75/3.5	85.5	14.89	96.02	16.67

TABLE II
Online results - Covert attention.

Subject	Nrep	RC speller P_{ac}(%)	RC speller PBR (bpm)	GIBS P_{ac} (%)	GIBS PBR (bpm)
S02	5	(a)		100	13.98
	3	-	-	84.2	13.43
S04	5	(a)		89.4	11.04

B. Online results

Four participants tested both paradigms using overt attention. Two of them, S02 and S04, underwent the second experiment were they tested both paradigms using covert attention. The participants had to spell the 19 character sentence 'THE QUICK BROWN FOX'. The results obtained with overt attention are in Table I. The averaged results, using the number of repetitions that maximizes the PBR, show that the performance achieved with GIBS, regarding accuracy and number of repetitions, is substantially better than that obtained with RC. The results are 14.89 bpm, 85.5% accuracy and 4.75 repetitions for RC speller, and 16.67 bpm, 96.02 % accuracy and 3.5 repetitions for GIBS. The results show that the classification improvements with GIBS were enough to compensate the occurrence of transitions between blocks, even reaching a PBR higher than that obtained with RC speller. As concerns the experiments based on covert attention, the online results are in Table II. None of the participants was able to control the RC speller. Participants reported that they were unable to perceptually attend the targets placed outer the center. On the other hand, both participants were able to covertly control GIBS with effective transfer rates. In Tables I and II, (a) means that participant was unable to perform the task, and (-) means that the experiment was not performed.

C. Offline analysis

To compare the P300 elicited in overt and covert attention experiments, we computed the averages taking the data collected during the calibration phases. Fig. 5 Top) shows the waveforms of the P300 average for GIBS. Both overt

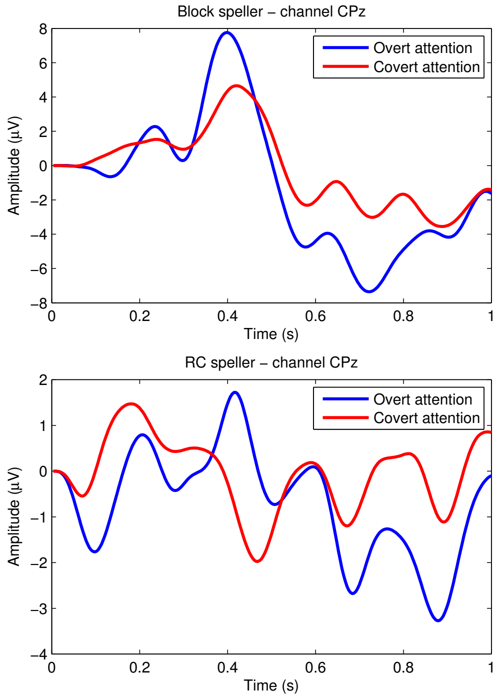


Fig. 5. P300 average for participant S02. Top) P300 waveforms for GIBS; Bottom) P300 waveforms for RC speller.

and covert experiments evoked a P300, and as expected the P300 with overt attention is higher. Fig. 5 Bottom) shows the waveforms of the P300 average for RC speller. The overt attention task elicits a P300, however there is no traceable P300 in the covert attention task. These results are consistent with the online results.

IV. CONCLUSIONS AND FUTURE WORKS

In this study, we proposed a novel Block speller paradigm called GIBS. The results show that GIBS can be controlled without moving the eyes (covert attention). This has particular relevance for individuals unable to control the movements of the eyes. On the other hand, a practical bit rate analysis showed that GIBS can achieve information transfer rates similar to those obtained with the standard RC speller. GIBS can still benefit from different arrangements of the letters within each group, further reducing the number of transitions.

To robustly assess the performance of GIBS, the experimental tests should be in a future work extended to a larger group of able-bodied and motor disabled individuals.

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