Calibration of the P300 BCI with the Single-Stimulus Protocol

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Abstract

For successful calibration of a P300 based brain-computer interface the user should not attend non-target stimuli. However, non-target stimuli automatically draw user's attention. To overcome this problem, we propose the use of the single-stimulus paradigm for calibration, at least in fresh users. In this simple paradigm targets are presented in absence of non-targets.

In the current study classifiers were trained on recordings made with either the single-stimulus protocol or with the usual P300 BCI protocol in the same participants, and applied online to detect an attended cell in a 3×3 matrix. Similar accuracy was observed for the new and the standard classifiers. This result are promising, as the single-stimulus paradigm should be easily understandable even without any previous BCI experience.

1 Introduction

In a typical visual P300 BCI discrimination between different possible inputs is based on the user's attention to one stimulus (the target) and his/her inattentiveness to the others. However, the non-target stimuli, acting as distractors, can automatically draw attention and evoke a brain response similar to the responses to targets [1].

This problem is especially serious during calibration of the BCI, when the user has no feedback showing whether the task is fulfilled correctly or not. The user's task is different from everyday experience, thus, the distracting power of the non-target flashes can be especially strong in a person without previous P300 BCI experience. Moreover, fresh users may easily misunderstand their task. If the user is a paralyzed patient, detecting such problems and helping the user to overcome them may require too high level of skills from the personnel. If the user is a video game player, he/she may try their first calibration sessions without getting well into all the details of the manual. Hence, there is a need for making the calibration protocol more robust in the face of real life situations.

Frye et al. [2] reported that suppressing stimuli at locations surrounding the target leads to the improvement of the calibration results (i.e., the accuracy of the subsequent BCI use). At further positions the non-target stimuli still were presented, so they, in principle, could capture attention.

The most radical solution can be removing the non-target stimuli completely from the calibration protocol. In addition to the absence of the distracting non-targets, this design and the related instructions could be much easier understood by the subjects, as they are required only to attend to stimuli which are themselves capturing their attention.

Although looking, for the first glance, not acceptable in the framework of the P300 BCI, this approach has a basis in psychophysiological studies, were the "single-stimulus" paradigm was found comparable to the standard oddball paradigm in its capacity to elicit the P300 wave [3, 4]. In our studies of modifications of the P300 BCI stimuli design the target-non-target difference in the P300 and occipital N1 were almost the same in single-stimulus and in row/column stimulation in a 3×3 matrix [5]. In addition, in a P300 BCI puzzle game proposed in [6] and implemented

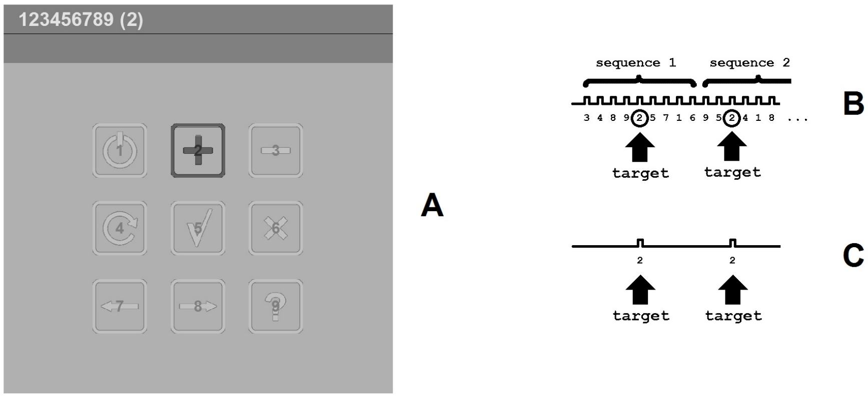

Figure 1: Stimuli in the single cell P300 BCI and in the new single-stimulus calibration protocol. (A) Stimuli matrix used in the current study, same in multistimulus (M-) and in the single-stimulus (S-)modes. (B) Stimuli time course in M-mode. (C) Stimuli time course in S-mode.

by A.Y.Z., S.L.S. and A.Y.K., the calibration was done with the usual protocol, but during the game the number of non-target items gradually decreased down to zero. It was tried by tens of novice players in public demonstrations, and the vast majority of them successfully assembled a full 4×4 puzzle matrix using it.

For classifier training, the EEG recorded at the positions where no stimuli are presented can be used instead of the EEG epochs following non-targets. The ground for this approach is provided by the fact that the amplitude of the responses to non-targets is usually low, and, therefore, the classifier's major task seems to be discrimination between the responses to targets and the background activity.

In the current study, we implemented, by modifying the open source BCI2000 software [7], and tested a single-stimulus modification of the P300 BCI calibration protocol.

2 Methods

Seven healthy participants (age 20–27) without previous experience with BCIs took part in the study after signing the informed consent. They viewed a 3×3 matrix with symbols and digits 1..9 overlapping the symbols (Figure 1 (A)).

In this study we compared the single-stimulus protocol with the single cell variation of the P300 BCI (e.g., [9]), in which the cells are highlighted independently of rows or columns, i.e., a stimulus is presented each time in one cell. Stimulation consisted of decreases of brightness (as, e.g., in [8]) of single cells for 128 ms with interstimulus interval 64 ms (see example in Figure 1 (A)).

We used two stimulus presentation modes: the multistimulus (M-) mode, and the single-stimulus (S-) mode. In M-mode, the stimuli were presented in all cells in a random order. A series of 9 stimuli presented once in each cell formed a sequence (Figure 1 (B)). In S-mode, the stimuli were presented only in the target cell (Figure 1 (C)). The distributions of target-to-target intervals (the time between the target and the preceding target) in S- and M-modes were approximately equal.

The current target cell number was indicated in the parentheses above the matrix (Figure 1 (A)). The order of targets was always 1,2, ..., 9; this sequence formed one block. The participants were asked to find in the matrix the digit shown in the parenthesis and to count silently "blinks" of the cell. Four stimuli sequences were presented per target in M-mode. In S-mode, four stimuli were presented per target. In the calibration phase, two blocks were presented in S-mode and two blocks in M-mode (participant #7 received three blocks per mode). In the test phase, all blocks were in M-mode.

Participant #	M	S	M*	S*	Sign(S-M)*	Abs(S-M)*
1	83	72	86	72	-	14
2	94	100	97	92	-	5
3	93	93	91	83	-	8
4	81	81	76	85	+	9
5	67	63	67	65	-	2
6	67	74	74	67	-	7
7	85	89	89	91	+	2
Mean (SD)	81 (11)	82 (13)	83 (11)	79 (11)		6 (4)
Median	83	81	86	83		7

Table 1: Accuracy (in %) for classifiers M (standard) and S (new). * - offline accuracy, which corresponded to the results applying the given classifier both to the data to which it was applied online and to the rest of the data.

EEG was recorded at Cz, Pz, PO7, PO8, O1, O2 against a joint reference at the earlobes with 250 Hz sampling rate. The data were low pass filtered, decimated down to 20 Hz and segmented in 50..750 ms epochs relative to stimulus onset. Channel amplitude data in each epoch were concatenated and formed a feature vector. Fisher Linear Discriminant Analysis was applied to these vectors for computing the classifier weights in S- and M-modes separately. We will further refer to the classifiers using these sets of weights as to S and M classifiers, respectively. In the case of S classifier training, the "non-target" epochs corresponded not to actually presented stimuli but to the positions at which they would be presented in M-mode.

In the test stage of the experiment, the task was the same as in the calibration phase, but this time the index of the cell recognized as attended was typed in the line below the target line. Thus, the participants could see whether they "typed" the digits correctly or not. M and S classifiers were randomly assigned to the blocks. The participants were not aware of which classifier was used in each block. Participants #1 and #2 received two blocks per classifier, typing 18 digits. The other five participants received three blocks per classifier and typed 27 digits. The S and M classifiers were also applied offline to the data from the same participants' test blocks recorded while the opposite types of classifiers (M and S, respectively) were applied in the online classification. This way, the size of the data used for computing each classifier's accuracy was doubled.

3 Results

Participant accuracies in the online and offline tests using both classifiers is shown in Table 1. On average, this group showed very similar accuracy for the standard and new protocols. The new protocol provided slightly lower accuracy comparing to the standard one, however, the difference was not significant according to Student's test for paired data ($t(6) = 1.27$, $p = 0.25$).

4 Discussion

The preliminary results obtained in this study are fully in line with our expectation that the P300 BCI accuracy would not deteriorate significantly if the classifier is trained using the single-stimulus protocol. They were obtained using the single cell variant of the P300 BCI and more testing is needed to determine if the single-stimulus protocol is also applicable to the more widely used row-column or new checkerboard protocols [10]. However, the single cell variant of the P300 BCI is also important, as being most practical when the number of commands is small (e.g., in wheelchair or robot arm control panels, or in video games).

In this study, we used relatively small number of trials for both classifier training and for online classification, to imitate regimes where the speed is more important than accuracy (e.g., in games). Additional testing might be needed to check the ability of the new protocol to provide high accuracy under conditions when higher number of stimuli repetitions is allowed. Attempts can be made to significantly reduce the trial-to-trial intervals for shortening time for calibration.

In addition, the similarity between the performance of classifiers trained in single-stimulus and in multistimulus modes suggest that single-stimulus paradigm should be also studied as a possible online classification paradigm, e.g., for BCI switches.

5 Conclusion

Our first results of testing the single-stimulus calibration protocol suggest that it may have a significant value for calibration of the P300 BCI, at least when it is used by fresh BCI users.

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