

A Fast “Single-Stimulus” Brain Switch

Anastasia A. Fedorova¹, Sergei L. Shishkin¹, Yuri O. Nuzhdin,¹
Marat N. Faskhiev^{1,2}, Albina M. Vasilyevskaya^{1,3}, Alexei E. Ossadtchi^{4,5},
Alexander Y. Kaplan³ and Boris M. Velichkovsky¹

¹ NBICS Centre, National Research Centre “Kurchatov Institute”, Moscow, Russia
anastasya.teo@gmail.com, sergshishkin@mail.ru, nuzhdin.urii@gmail.com,
velich@applied-cognition.org

² Faculty of Physics, Lomonosov Moscow State University, Moscow, Russia
liquidmole@mail.ru

³ Faculty of Biology, Lomonosov Moscow State University, Moscow, Russia
albina-vasil@mail.ru, akaplan@mail.ru

⁴ Centre for Cognition and Decision Making, National Research University Higher School of
Economics, Moscow, Russia

⁵ St. Petersburg State University, St. Petersburg, Russia
ossadtchi@gmail.com

Abstract

We present a novel brain switch that enables sending an urgent command in asynchronous mode at a relatively high speed and accuracy. Five able-bodied participants issued a command to a moving robotic arm in 4 s with only 0.1 false activation per minute. Even higher speed was observed in less demanding condition of an image inspection task, as well as in an offline test with a hybrid BCI design including a saccade detector.

1 Introduction

The need for a fast brain switch emerges in the development of brain-computer interface (BCI) control for assistive robotic devices. While low speed and impreciseness of noninvasive BCIs can be, to a large extent, compensated by assigning the low level control to robotic intelligence, the user must be given an opportunity to rapidly stop an action if something goes wrong [3]. A BCI for this function (a fast “brain switch”) should possess the following features: (1) be as fast as possible, (2) be asynchronous, i.e. able to detect the user’s intention at any time moment, (3) have a low false activation rate (FA). An ability to detect a command irrespective of the preceding activity in which the user was involved is also desirable.

Rebsamen et al. [3] proposed a fast asynchronous switch based on a modified P300 BCI. In their design, stimuli were presented in a 3x3 matrix, but a command could only be issued using attention to the central stimulus. Robotic wheelchair was stopped with mean response time (RT) of 6.0 s and FA of 1.2 per min. In [1], the P300 BCI was combined with steady-state visual evoked potential (SSVEP) based BCI, providing RT of 5.3 s and FA of 0.5 per min.

One may ask if the non-target stimuli (8 of 9 stimuli in [3] design) can be removed from the P300 BCI stimulus sequence, to improve the conditions for perceiving the target stimuli and make possible its fast presentation. Although the absence of non-targets contradicts the traditional view on the P300 BCI, we demonstrated that a simplified and more ergonomic variant of the P300 BCI without non-targets can be successfully used for calibrating a classifier for a normal P300 BCI [6]. Using this approach, reminiscent of the “single-stimulus paradigm” known in psychophysiology [2], we designed a new “single-stimulus switch”. In offline simulation using data from four participants, the BCI classifier exceeded the threshold already about 2 s after a saccade to the stimulus, with FA rate of 1.2 to 3.4 per minute [5].

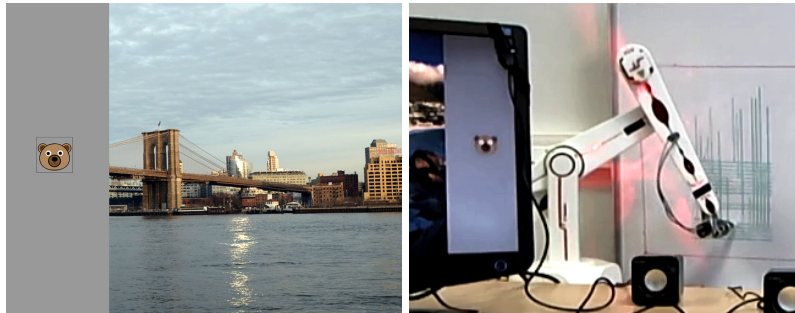


Figure 1: Left: A screenshot from the auditory feedback phase. Right: a view from behind the participant in the robot control phase.

In the current study, the “single-stimulus switch” was tested online for the first time. To demonstrate the effectiveness of the switch in diverse conditions, we tested it in two tasks. In these tasks, the participants were involved into different types of visual activity (still image inspection task and passive pursuing a moving robot arm) from which they had to switch urgently to BCI control at unpredictable time moments.

2 Methods

Five healthy volunteers participated in the study. EEG was acquired from Cz, Pz, POz, P2, Oz, O1, O2 locations. We used BCI2000 system [4] with our module for “single-stimulus” presentation and online processing. Stimuli were stylized animal faces presented for 150 ms with interstimulus interval varied from 300 to 550 ms.

For calibration, the participants silently counted stimuli (8 “control” runs, each consisted of 8 blocks of 8 stimuli with 2 s pauses between blocks) and silently read a text (a 10 min “non-control” run). Rebsamen et al. [3] found no difference between reading and other conditions without stimuli counting when they represented the “non-control” condition in estimating classification performance of their BCI in similar settings. We chose the reading task because it is simple and can be well controlled. 512 epochs of 700 ms length were extracted from the “control” EEG starting from the stimulus. From “non-control” EEG, 598 epochs of the same length were extracted with fixed 300 ms interval between them. The EEG was downsampled to 50 Hz and the channel data were concatenated, resulting in feature vector length of 245. Fisher Discriminant Analysis with Tikhonov regularization (ridge regression) was applied to “control” and “non-control” epoch sets to compute the classifier weights.

In the subsequent two phases of BCI online testing, the stimuli (one of the animal faces used in calibration) were presented with the same interstimulus interval, but without 2 s pauses. Each time a stimulus-related EEG epoch was obtained after a new stimulus, the classifier was applied to an average of the last five stimulus-related epochs and its output was compared to a predefined threshold. Once the threshold was exceeded, the BCI was “activated”, i.e. caused actions specific for each testing phase (see below). Data from the first 3 min run (not used in the analysis of the BCI performance) were used to adjust the threshold so that RT and FA were minimized.

In the auditory feedback phase, the background task was to guess what cities were shown on the screen (Figure 1, left). A photo on the screen was changed each 60 s. A sound signal was

presented at random moments. After this “signal event”, the participant had to start counting stimuli until he or she heard a recorded voice saying “Yes” and the stimulus was replaced by a green circle. In the robot control phase, the participants watched a robotic arm (AREXX Mini Robot Arm in the first two experiments and ST Robotics R12-six in the last three experiments) at 1.5 m distance (Figure 1, right). The robot made fast movements (Mini Robot Arm was waving its hand and R12-six was drawing a horizontal line) until it suddenly changed movement direction (a “signal event” in this phase). When this occurred, the participant had to “stop” the robot as fast as possible by counting the stimuli until the green circle appeared and the robot returned to its “normal” behavior.

The BCI activation was considered as correct if it occurred between 750 ms and 8 s after the “signal event”, and as a false activation otherwise. RT was computed for correct activations as their time relative to the preceding “signal events”. FA was computed as the false activation number divided by duration of testing, and miss rate was computed as the proportion of “signal events” not followed by a correct activation. In an additional analysis, a hybrid EEG and EOG based command detection was simulated, with number of averaged EEG epochs decreased from five to three. Large saccades in the direction of the stimulus were detected in EOG using a combined threshold-based and template-based detector and used to confirm activations: BCI threshold exceeding produced a command only if preceded by such a saccade.

3 Results and Discussion

In the auditory feedback phase, mean RT was 3.7 s, FA was 0.3 min^{-1} and miss rate was 0.1. In the robot control phase, mean RT was 4.0 s, FA rate was 0.1 min^{-1} and miss rate was 0.1.

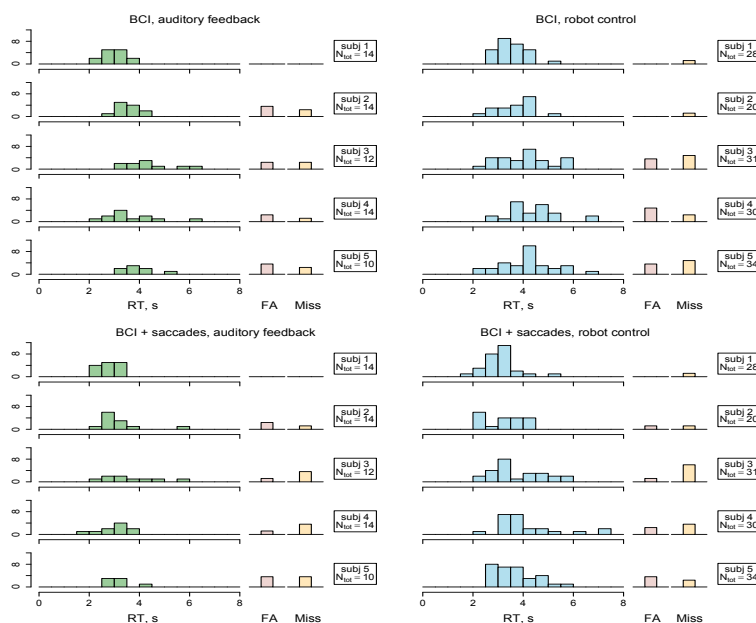


Figure 2: Distribution of Reaction Times (RT), False Alarms (FA) and Misses in online (BCI) and offline (BCI + saccades) tests. Here, FA and Misses data are not normalized. The y-axis shows the number of observations, while N_{tot} is the total number of “signal events”.

In offline simulation of hybrid EEG-EOG-based command detection, mean RT was reduced to 3.1 s and 3.6 s for the auditory feedback and robot control phases, respectively. FA was 0.2 min^{-1} and 0.1 min^{-1} in the auditory feedback and robot control phases, respectively. Miss rate was 0.2 and 0.1, respectively (Figure 2, lower row).

This study demonstrated improvement of the BCI switch online performance in issuing an urgent command to a robotic device comparing to the previous online results [3][1]. FA was low even in the image inspection task (the auditory feedback phase), where gaze and attention could be easily attracted by the stimulus positioned near the inspected picture (Figure 1, left).

Further improvement of the initial results obtained in this study can be expected, in our view, by improving the classifier (e.g., by automatic adjustment of the regularization parameter and the threshold) and optimizing parameters of stimulation. Additional possible way for performance improvement can be the use of a committee of classifiers trained on “control” epochs with different overlap between the responses to stimuli and/or several non-control conditions related to different scenarios (e.g., fixating a position close to the stimuli but without attending them). Hybridization of the “single-stimulus” BCI with saccade detection also seems promising, particularly with implementation of advanced saccade detectors and a Bayesian approach to BCI and saccade data fusion.

Acknowledgements

Part of this study related to the hybrid EEG and EOG based command detection was supported by Russian Science Foundation Grant 14-28-00234.

References

- [1] Y. Li, J. Pan, F. Wang, and Z. Yu. A hybrid bci system combining p300 and ssvp and its application to wheelchair control. *IEEE Transactions on Biomedical Engineering*, 60(11):3156–3166, 2013.
- [2] J. Polich and M. R. Heine. P300 topography and modality effects from a single-stimulus paradigm. *Psychophysiology*, 33(6):747–752, 1996.
- [3] B. Rebsamen, C. Guan, H. Zhang, C. Wang, C. Teo, V. M. H. Ang, and E. Burdet. A brain controlled wheelchair to navigate in familiar environments. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 18(6):590–598, 2010.
- [4] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw. Bci2000: a general-purpose brain-computer interface (bci) system. *IEEE Transactions on Biomedical Engineering*, 51(6):1034–1043, 2004.
- [5] S. L. Shishkin, A. A. Fedorova, Y. O. Nuzhdin, I. P. Ganin, A. E. Ossadtchi, B. B. Velichkovsky, A. Y. Kaplan, and B. M. Velichkovsky. Towards high-speed eye-brain-computer interfaces: combining the single-stimulus paradigm and gaze translation (in russian). *Herald of Moscow University, Ser. 14: Psychology*, (4):4–19, 2013.
- [6] S. L. Shishkin, A. A. Nikolaev, Y. O. Nuzhdin, A. Y. Zhigalov, I. P. Ganin, and A. Y. Kaplan. Calibration of the p300 bci with the single-stimulus protocol. In *Proceedings of the 5th International BCI Conference*, pages 256–259, 2011.