From BCI Training to Successful Application Control

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Abstract. Successfully operating applications—like telepresence robots or text entry systems—just with your mind requires a good level of Brain-Computer Interface (BCI) control. How much training is needed to achieve such a level? Is it possible to train a naive end-user subjects in 10 days to successfully control such applications? In this work we report our mid-term experiences based on the training of 12 severely motor disabled participants at a rehabilitation clinic, without BCI experts present.

Keywords: BCI, EEG, Motor imagery, Single trial performance

1. Introduction

Brain-Computer Interfaces (BCIs) are no longer only used by healthy subjects under control conditions in laboratory environments, but also by patients, controlling applications in their homes. But how much BCI training is needed to achieve a reliable control of an application? In this paper we want to share the experiences we gained, by starting with naïve participants, teaching them first to achieve BCI control, evaluating the performance through online BCI experiments and finally controlling two applications (a telepresence robot and a text entry system). The aim was to do this in 10 days, working together with a therapist at a rehabilitation clinic and without any BCI experts present!

2. Material and Methods

In this work, the participants had to start by imagining left hand, right hand and foot movements during calibration recordings. Afterwards the two most discriminable tasks were used for a 2-class control experiment; either for the online feedback experiment or for controlling the two applications.

2.1. Brain-Computer Interface

The brain activity was acquired via 16 EEG channels over the motor cortex. From the Laplacian filtered EEG, the power spectral density was calculated. Canonical variate analysis was used to select subject-specific features, which were classified with a Gaussian classifier [Galán et al., 2008]. Decisions with low confidence on the probability distribution were filtered out and evidence was accumulated over time. The BCI training was performed at the clinics without BCI experts present. Only the classifier setup was done remotely by the BCI expert, so no complex task had to be performed at the patient’s place. Therefore we created a remote support platform [Leeb et al., 2011] which allows either to transfer files, provides communication or a remote takeover in case of technical problems.

2.2. Application Prototypes

Since the goal of the BCI is not to control a cursor on a computer screen, but instead is to be used by the patient to interact with the surrounding world, we tested two different applications. The first application was a text entry system called BrainTree [Perdikis et al., 2012]. Using a series of left and right BCI commands the participants could select letters out of an alphabetically sorted tree. The visualization implements a so-called Hu-Tucker binary tree (based on a language model) which ensures an optimal but not equal number of commands to reach each character. The second application was a telepresence platform based on the Robotino robot [Carlson et al., 2012]. The subject remotely controlled the robot, steering it to the left or to the right to reach several targets within an office environment. In addition, the subject can intentionally not deliver any mental command to activate the default behaviour of the robot, which consists on moving forward and avoiding obstacles with the help of a shared control system using its on-board sensors. The subjects saw a video-transmission from an on-board camera of the robot in parallel with the BCI output. Both applications were quite demanding for the subjects, since besides the increased workload and the split attention between the BCI and the application, it was also necessary to perform the requested BCI action with certain temporal precision.
3. Results

Up to now, 12 end-users aged 46±12 years (3 female) have participated once every 1–2 weeks for up to 3 hours/day. Six subjects (S1–S6) had a very good level of control and could test the applications; three did not reach that level within 10 sessions (maximum possible amount). In the case of one subject (S8) we had technical problems and two subjects (S10, S12) had to be excluded during the trainings process because of inherent muscular artefacts due to their impairments. The subjects are affected by different levels of myopathy (4), spinal cord injury (6), tetraplegia (1), or spino-cerebellar ataxia (1). Since the whole experiment was limited to 10 days, not all subjects could test the text entry application.

Figure 1 shows the performance of the online BCI runs using the Youden index YI (1), whereby YI=1 means perfect control and 0 equals chance level:

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YI = \text{Sensitivity} + \text{Specificity} - 1 = \frac{TPR}{TP + FN} - \frac{FPR}{TN + FP}
\]

The performances of the applications (see Fig.1) are reported for the text entry as the percentage of correctly written characters compared to the total number of written characters [Perdikis et al., 2012], and for the telepresence platform as the ratio between the time needed to reach the targets with BCI control vs. manual control [Carlson et al., 2012], both resulting in 1 for perfect and 0 for no control.

4. Discussion

All subjects who achieved good BCI performance, could also control the applications successfully (see Fig.1). Especially whenever end-users reached a YI >0.6, they mastered the applications equally well as healthy subjects. This is very important, because having a good BCI control does not guarantee good control over the application, due to the necessary split attention between the application and the BCI. Furthermore, BCI training does not require users to achieve 100% performance every trial, but most applications demand almost perfect performance all the time [Leeb et al., 2011]. Unfortunately only 50% of the participants could test the applications. Due to the strict time limitations of our experimental protocol, we had to stop the training process of those end-user who didn’t reach a YI >0.4 over two consecutive sessions after 10 days. The performance drop of subject S2 in case of Robotino resulted from one single run, in which she intentionally delivered wrong commands believing that the target was somewhere else. Finally, control of the applications could be improved by the use of a hybrid BCI, where key commands (e.g. error correction, pause…) are delivered through other channels such as residual muscular activity [Perdikis et al., 2012].

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References


