DOI: 10.3217/978-3-85125-682-6-20

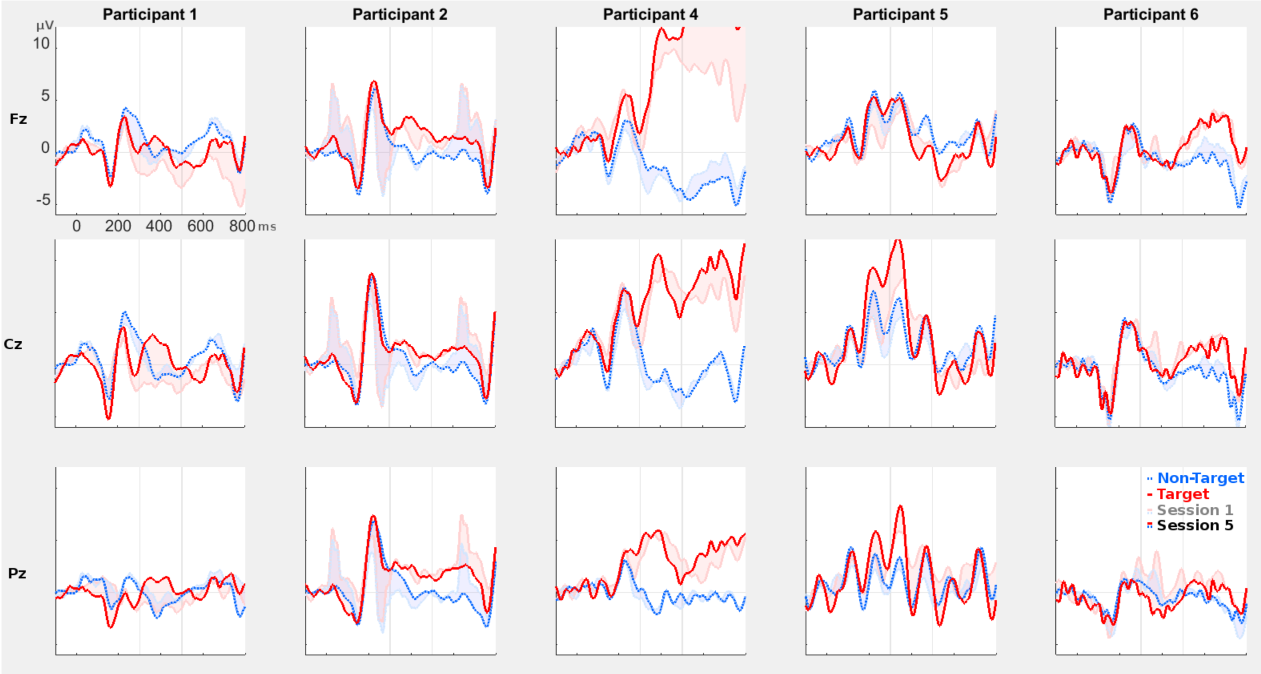

Figure 1: Post-stimulus epochs on sessions 1 (light colours) and 5 (bold colours) at positions Fz, Cz, Pz.
Target stimuli (red) appear to have elicited a positive deflection in the P300 range. Participant 6 appeared to have a delayed ERP deflection after about 450ms. Data was averaged by participant and additionally lowpass-filtered (20Hz, for visualization only). Positivity up.

During three calibration runs at the beginning of each session, participants had to concentrate on each of the body positions several times, resulting in a total of 240 target and 720 non-target epochs. These data served to train a linear classifier which was then used for two free navigation runs. Here, participants had to navigate a wheelchair through a virtual 3D apartment along three checkpoints by selecting a direction and then focusing on the corresponding body position (i.e. left knee to make a left turn). After the first run, starting and end points of the course were switched, so that participants had to navigate back to the original starting point. One successful run required at least 14 commands, however, erroneous or misleading commands were also executed and had then to be corrected. Thus, a maximum number of 22 commands, roughly corresponding to the number necessary when assuming the minimum accuracy of 70% for sufficient control [11], was allowed before the run was terminated.

To preclude possible ceiling effects like in an earlier study from Herweg and colleagues [1], which always used 8 stimulus repetitions for one selection, the number of repetitions was kept at a minimum for each participant and for every session.

We estimated the number necessary to reach 100% classification accuracy via visual analysis and predictions from the classifier algorithm. This stimulus number was determined for every participant and every session and then used for the free navigation task.

After each session, to assess workload, the NASA TLX

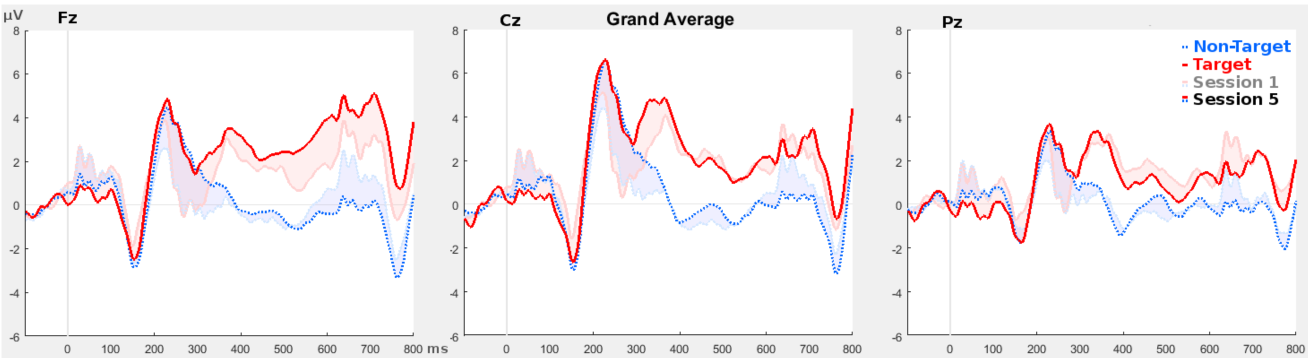

Figure 2: Grand averages of post-stimulus epochs at Fz, Cz and Pz positions. Target stimuli elicited P300 ERPs at all electrode positions. Descriptively, the ERP amplitudes have increased in magnitude from session 1 (light colours) to session 5 (bold colours) at position Fz. Overall, both amplitudes and MD appear strongest at Fz and Cz, but ERPs are still visible at Pz. Data was averaged over all participants. Positivity up.

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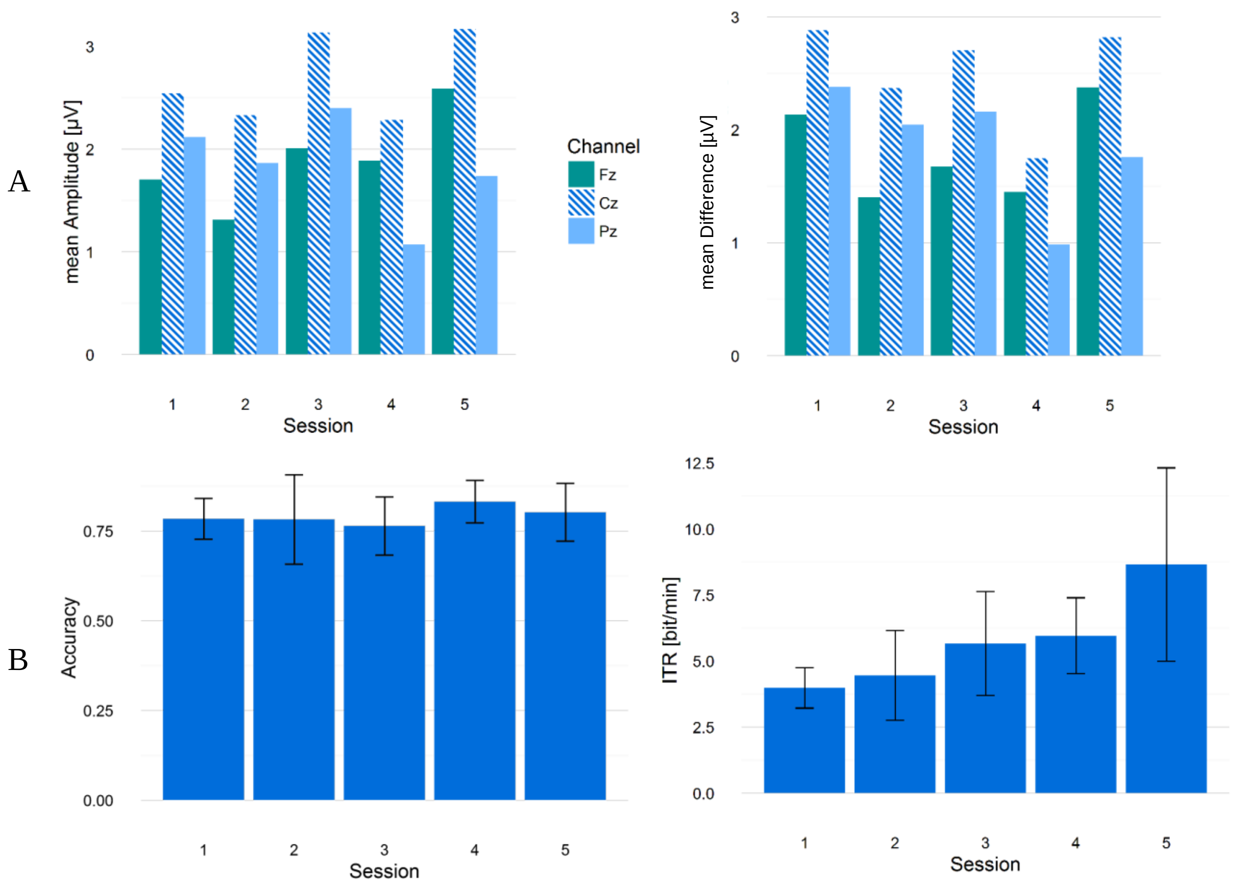

Figure 3: Bar plots of dependent variables over the course of the 5 training sessions. Data was averaged over all participants (Error bars represent SE).
A) Physiological measures, amplitude and MD, split by electrode position. Visual analysis revealed no obvious effects.
B): BCI performance measures. Online accuracy does not appear to increase with training, while ITR does appear to increase.

[12], and after the first and last session the adjusted QUEST [13,14], to assess satisfaction with the device, were filled out by the participants (Results not shown here).

EEG processing: EEG data was band pass filtered between 0.1 and 30 Hz and divided into segments of 800 ms post-stimulus, plus another leading 100 ms that was used for baseline-correction. Segments containing values exceeding ±150 µV were excluded as artifacts. Target and non-target epochs were grouped and then averaged separately. This process was performed with MATLAB© (v2013b) using functions provided by BCI2000 [15] and EEGLab [16]. Using a step-wise linear discriminant analysis as implemented in the BCI2000 package, we built new classification models for each session.

Data analysis: The use of BCI accuracy (i.e. the percentage of correct classifications) as the sole comparative measure of performance is not sufficient when the number of stimuli differs between groups or time points. Thus, we also used the ITR as a dependent variable. This ITR, given in bits per minute, is used to calculate the amount of information transferred during a given time. The number of bits (B) can be calculated with equation 1 using the accuracy (P) as well as the number of all possible selections (N = 4).

$$B = \log_2 N + \mathrm{P}\log_2 P + (1-\mathrm{P})\log_2\frac{(1-\mathrm{P})}{(\mathrm{N}-1)} \qquad (1)$$

The ITR is then calculated by dividing the number of bits by the time necessary for the selection. It is thus directly dependent on the number of stimuli repetitions, but also takes accuracy into account.
Additionally, we extracted physiological features (mean target amplitudes and mean difference between target and non-target) from the EEG data from a time window ranged 300-500ms post-stimulus.
Due to the small sample size, results will be reported descriptively.

RESULTS

Wheelchair navigation through the virtual apartment was achieved with an average online accuracy of 78.5% (sd=14.8).
Target and non-target epochs from the three calibration runs at the beginning of each session are presented in

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Figure 1. Visual inspection revealed a positive deflection in the P300 range at positions Fz, Cz and Pz (most pronounced at Fz) in some (1,2,4) subjects. Participant 6 had a positive deflection at a latency of around 450 ms.
Grand averages of these epochs are shown in Figure 2. Here, visual analysis again reveals a putative P300 deflection which was most pronounced at Fz and Cz and that appeared to increase with training (Session 1 vs. Session 5) at Fz.
MD at Fz increased from 2.14 to 2.37 µV. At Cz, values remained more or less stable (2.88 to 2.81 µV), whereas at Pz, values decreased (2.38 to 1.76 µV). Mean amplitude at Fz increased from 1.70 to 2.59 µV, at Cz from 2.54 to 3.17 µV but decreased at Pz (2.12 to 1.74 µV).
Accuracies (P=0.79; sd=0.15) from the navigation task were used in conjunction with the respective number of stimulus repetitions to calculate the individual participant's ITRs. Averaged online accuracies and ITRs are shown in Figure 3. There appears to be a strong trend of increasing ITRs, but not accuracies, with session numbers. Average ITR was 4.0 and 8.7 bits/min on sessions 1 and 5, respectively.

DISCUSSION

Five participants navigated a wheelchair through a virtual apartment with a reasonable level of BCI control. With a mean accuracy of 78.5%, participants mostly exceeded 70%, a number which is considered the low threshold for efficient BCI control [11]. Stimulus repetitions for each session were kept deliberately low to preclude any ceiling effects as experienced in [1], so we expect accuracies to be higher when increasing the number of stimuli used for a selection, albeit at the cost of speed.
Descriptively, mean ITR increased substantially over the 5 training sessions, with session 5 resulting in more than double the ITR as compared to session 1. Overall, this shows that participants achieved the same accuracy in less time (i.e. with fewer stimulus repetitions). We speculate that our hypothesis that ITR would increase with training might be confirmed. Since stimulus repetitions were individually adjusted, average accuracies remained consistent over the sessions. However, their comparatively [1] low values indicate that we set the number of stimuli too low.
The two physiological variables, mean amplitude and MD, did not reveal an overt training effect on the individual level, although a trend may be seen, specifically at position Fz. Our hypothesis about increasing physiological measures is thus far not supported.
The apparent training effect (as seen in ITR increase) seems not to be reflected in the physiological measures. This may be because traditional analysis struggles to accommodate for deviations in individual participants' ERP pattern, e.g. in cases of unusually high latencies or inversed polarities. This illustrates the need of machine learning approaches that automatically detect spacial and temporal features on an individual level and explains why an effect of session number is visible on machine learning-dependent variables such as ITR, but not in static measures such as amplitudes derived from a fixed time and position.

CONCLUSION

We have again shown that wheelchair control with our tactile BCI paradigm is feasible and that training effects (as measured via ITR over the five sessions) appear to be present. We will continue to recruit more subjects for the present study to allow for statistical analysis and to investigate whether the results from the study of Herweg and colleagues [1] are replicable. So far, all our dependent variables remained below the values achieved in [1].

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