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TACTILE BRAIN-COMPUTER INTERFACE CONTROL OF A MOBILE PLATFORM IN A REAL WORLD ENVIRONMENT USING A LOW-COST ELECTROENCEPHALOGRAPHY HEADSET

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ABSTRACT: We used a brain-computer interface (BCI) system controlled with event-related potentials (ERPs) evoked by tactile stimulation to control a mobile platform.

Eight tactile stimulators were attached in four pairs to the arms, legs and back of the participants (N=12). The electroencephalogram (EEG) was recorded via a modified Emotiv headset. All participants were trained in the laboratory, then four participants controlled the mobile platform in an outdoor environment.

Inside the laboratory the participants achieved average accuracies of 72%. Outside four participants achieved average accuracies of 61% (range 52-88%).

Technical problems with the responses of the mobile platform and high outside temperatures prevented higher levels of control with the mobile platform. A mobile platform better suited for the discrete control implemented with the BCI or a different control scheme will be needed for future experiments. Nevertheless, subjects were able to control the mobile platform with tactile ERPs using low-cost EEG equipment in a real world environment.

INTRODUCTION

Since the first demonstration of Farwell and Donchin that the visual P300 event-related potential (ERP) component of the electroencephalogram (EEG) can be used to control a brain-computer interface (BCI) the usefulness of this method for communication has been shown in numerous studies, also with persons with severe motor impairments [1, 2]. Another application in which assistive technologies, such as BCIs, have the potential to improve the quality of life of persons with disabilities is personal mobility. Control of mobile platforms with BCIs has been shown mostly using motor imagery (see e.g. [3]). The disadvantage of this approach is that control over more than two classes is difficult to obtain without a long training period. A potential alternative are P300 BCIs that do not rely on visual stimulation and thus leave the visual channel unoccupied to observe the environment [4]. In studies using a simulated wheelchair tactile evoked ERPs were shown to be a viable control method with four classes [5]. In the current study we used a modified Emotive headset (see [6]) to control a physical mobile platform [7, 8, 9] in an outdoor environment using the same setup as in [5].

MATERIALS AND METHODS

We recruited twelve healthy participants (six female, average age 23.4 SD 3.4, range 20-32) without a history of neurological or psychological disorders. Participants signed informed consent and were compensated with € 8 per hour. None of the participants had experience with tactile P300 BCIs, six of the participants had experience with visual P300 BCIs.

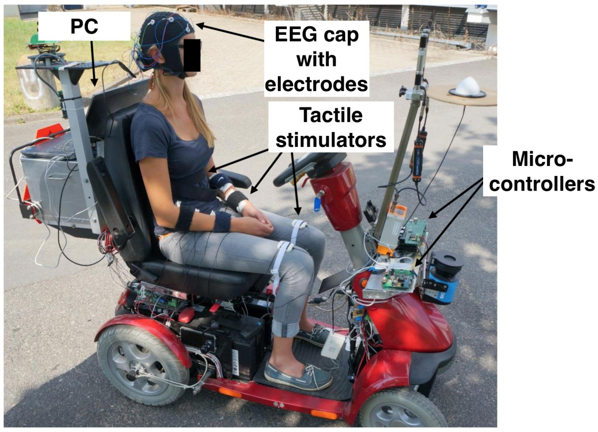

Figure 1: Setup used to control the mobile platform. The control PC received the EEG data from the modified Emotiv headset, classified the data and sent commands to the microcontrollers that controlled the mobile platform. Eight tactile stimulators were attached two to the left arm, two to the right arm, two to the left leg and right leg and two to the back.

Eight tactile stimulators (C2 Tactors, Engineering Acoustics Inc., Casselberry, USA) were attached in pairs, as suggested in [5], to the arms, legs and back of the participants (see Figure 1). To steer to the left the participants attended to the stimulators on the left arm, to steer to

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the right the participants had to attend to the stimulators on the right arm, to move forward to the stimulators on the legs and to move backwards to the stimulators on the back. The stimulators were placed at least 10 cm apart. The stimulus duration was set to 250 ms with a frequency of 250 Hz and an inter-stimulus interval of 375 ms. For one selection each pair of stimulators was activated ten times. Between selections there was a pause of five seconds to give the participants enough time to choose the next command to attend to. Participants were seated in a comfortable chair in a quiet room and received verbal feedback on the selected direction.

For calibration each of the four directions had to be chosen twice (eight selections) in one run. A total of three runs were performed for calibration (24 selections). Based on this calibration data a classifier was trained using stepwise linear discriminant analysis (SWLDA; forward $p < 0.1$, backward $p > 0.15$, 60 features). The data was segmented into 800 ms epochs and subsampled to 16 samples.

After calibration the participants were asked to perform another two runs with a total of twelve selections (the participants were asked to “copy” a specific sequence of twelve commands) and a third run in which they had to plan a route and choose the appropriate commands themselves (the participants were asked to “drive” the mobile platform from a starting to an an end point shown to them on a piece of paper).

Four participants with over 90% accuracy in the previously described tasks participated in a second experiment in which the physical mobile platform was controlled. The calibration for this task was performed in a large hall in which also other activities were taking place. Thus the environment was noisy. The driving task was performed outside. Outside it was quiet except during the experiment of participant six (construction noise). The participants performed the same calibration task as in the previous experiment while seated in a chair and selected five commands to confirm that the calibration was successful. Participant three was chronologically the first participant to perform the driving task (participant twelve the second, participant two the third and participant six the last). Due to a higher amount of noise when operating the BCI in the hall where the calibration was performed a 9 Hz low-pass filter was activated for all participants after participant three. Then the participants were asked to move outside to the start position of the route that was to be navigated with the mobile platform. While the mobile platform was controlled with the BCI one of the experiment supervisors held an emergency stop button. The last two participants first controlled the mobile platform with a keyboard to gain familiarity with the behaviour of the mobile platform and the route. From the starting position the participants drove around a patch of grass and back to the starting position. If this was not accomplished with 60 commands the experiment was aborted. The optimal path needed 36 correct selections. The mobile platform was configured to change the angle of the steering wheels if the left or right command was chosen. Choosing forward or backward would move the mobile platform in the corresponding direction for approximately one meter.

Leave one-run-out cross validation accuracy was calculated for the four participants that performed both sessions (training and driving) also using SWLDA. ERP analysis was also performed on the calibration data because this is the only data with target markers in the second session (the driving task was performed without predefined selections).

The EEG was recorded using 14 passive Ag-AgCl electrodes placed in plastic holders in an elastic EEG cap (Easycap GmbH, Herrsching, Germany). The electrodes were positioned at Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, PO7, Oz and PO8 with the ground at AFz and the reference on the right mastoid. The amplifier was a modified version of an Emotiv EPOC headset (EMOTIV Inc, San Francisco, California, USA), for a description see [6]. The amplifier was connected via bluetooth to BCI2000 [10]. The output of the classifier was sent to the mobile platform via a python script. The EEG was sampled with 128 Hz, notch filtered at 50 Hz and additionally bandpassfiltered from 0.1-30 Hz (for the driving experiment of participants two, six and twelve this was set to 0.1-9 Hz).

RESULTS

While performing the training in the laboratory the averaged accuracy of the twelve participants during the selection task with predefined commands was 72.2%. Two participants reached 100% and eight participants accuracies over 70%. The accuracy decreased to an average of 55% during the task in which the participants had to plan the route themselves. Five participants achieved accuracies of 70%. Participants two (average accuracy both tasks 80%), three (86.7%), six (75.2%) and twelve (100%) took part in the second session to control the mobile platform in an outdoor environment. For a summary of the accuracy of all participants see Figure 2. The dependency of the accuracy on the number of stimulus repetitions for the four participants that performed both training and driving is shown in Figure 3. Only participant twelve would have been able to control the mobile platform with a lower number of stimulus repetitions.

The participants needed between 36 and 57 minutes to make 60 selections (the maximum until the experiment was aborted) on the outside course. None of the participants reached the end point of the course. During the experiment conducted with participants two, three and six the outside temperatures were around 30 degrees Celsius and the sun was shining. The first participant of the outside driving task (participant three) expressed that the sun did not bother her, nonetheless the subsequent participants were shielded with an umbrella. During the experiment with participant twelve the sun was behind clouds. Participant two performed 65% of the selections as intended. The experiment was interrupted once to correct

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the angle of the steering wheel.

Participant three performed 65% of the selections as intended and the emergency button had to be pressed twice to prevent collisions with the sidewalk. Twice the mobile platform did not move backwards even though the correct command was selected.

Participant six performed 52% of the selections as intended. A possible negative influence may have been construction noise 100 m away from where the experiment was conducted.

Participant twelve performed 88% of the commands as intended. The mobile platform had to be reset during the task due to the battery indicator erroneously showing a charge state of 0%. Twice the emergency button had to be used to prevent collisions. Five selections of the command move to right direction were not executed by the mobile platform. After a second reset the problem was resolved.

ERP data of the target responses in the calibration data of the four participants that performed the outdoor driving task is shown in Figure 5.

All participants said they found the control of the mobile platform to be intuitive and felt to be in control during the experiment. The particularly enjoyed the realistic setting. All participants expressed their frustration about the mobile platform not always executing the selected command.

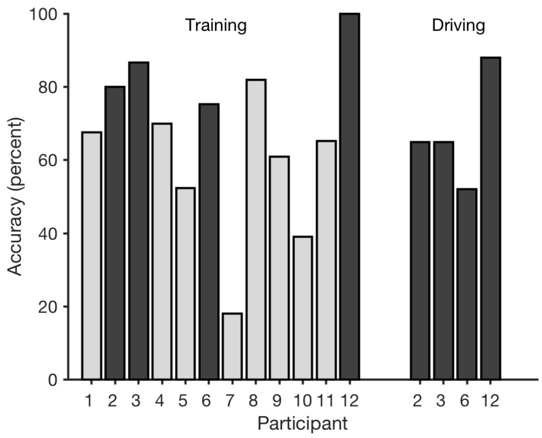

Figure 2: Online accuracies of the participants during the training task (left group of bars) and during the driving task (right group of bars). Participants selected for the driving task are shown in dark gray. Accuracy is the average of all tasks excluding calibration.

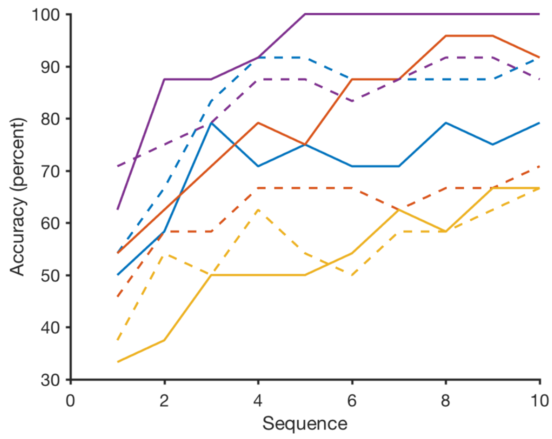

Figure 3: Offline accuracies of the participants that performed training (dashed line; session one) and driving (continuous line; session two) tasks. The accuracies were calculated using the calibration data. Accuracy is shown per sequence (i.e. the number of stimulus repetitions; higher number of repetitions increase the signal to noise ratio of the ERP compared to the background EEG but also increase selection times). Participant two in blue, participant three in red, participant six in yellow and participant twelve in purple.

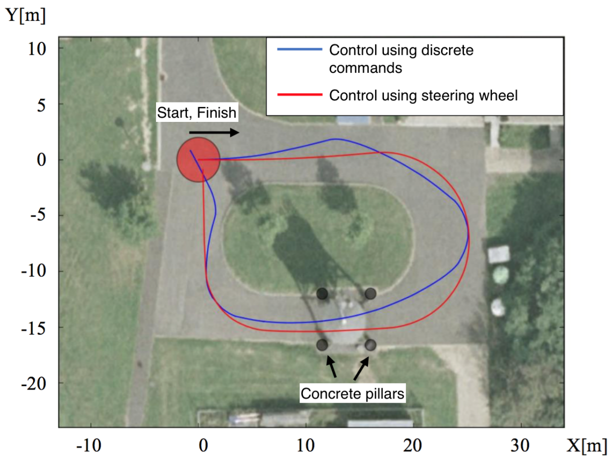

Figure 4: The area where the outdoor experiment was conducted. Participants started at the location indicated by the red circle. The paths shown are an exemplary path using the steering wheel of the mobile platform (red) and a path using keyboard control to give discrete commands analogous to the BCI experiment (blue). Trajectory data during the BCI experiment is not avaliable. The satellite image was obtained from Google Maps.

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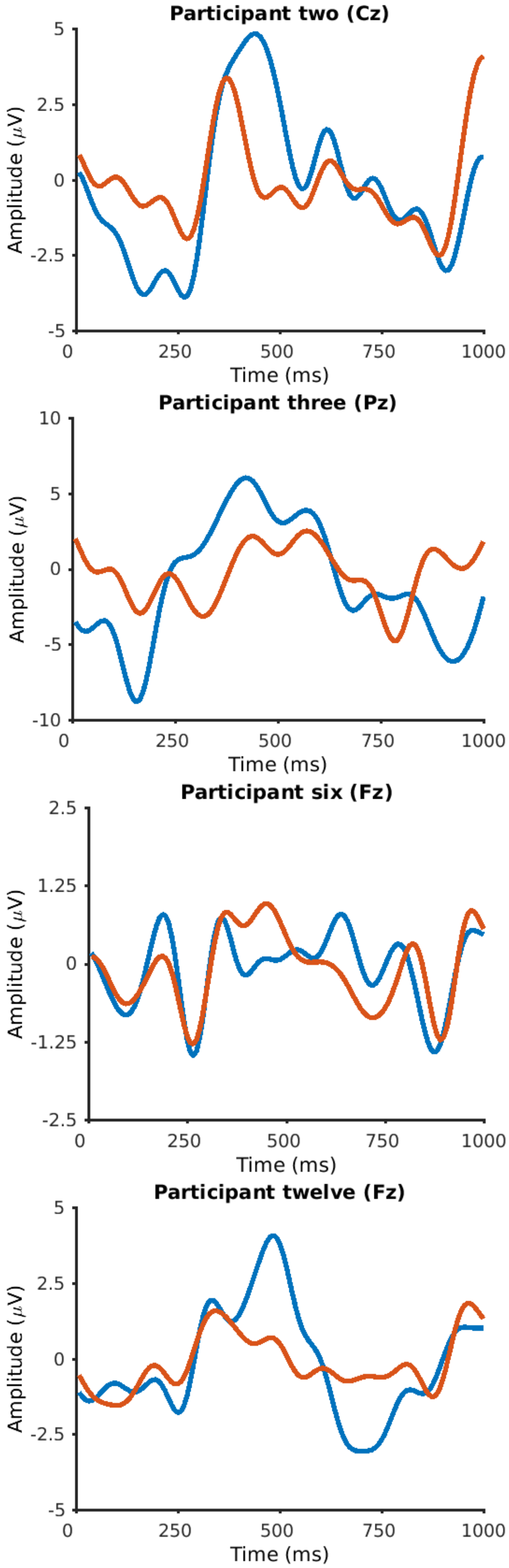

Figure 5: Exemplary event-related potentials based on the calibration data from session one of the four participants that performed the outdoor experiment in session two. The blue line shows the the target response, the red line the non-target response. Note that amplitude scales and channel location differ between participants.

DISCUSSION

With 72% the average accuracies across all twelve participants would have been sufficient to control the BCI. Task difficulty appears to have had an effect on performance in our sample as the accuracy decreased to 55% when the participants had to plan the path themselves. Considering the EEG hardware that was used the 62% average accuracy the four participants that performed the outdoor driving task achieved are comparable to the 69% in a binary choice task also using the modified Emotiv and conducted outdoors that was reported in [6]. The stimulation unit that was used in the current study was also used for control of a virtual wheelchair inside the laboratory and the accuracies were higher with on average 85% [5]. In the current study, the EEG recordings showed a lot of noise in the environment of the hall where the calibration for the driving task was conducted in the second session and the low-pass filter was reduced to 9 Hz for three of the four participants in this session. It is uncertain whether such problems may have been avoided with another amplifier as other studies using a similar paradigm were conducted in a lab environment [5].

Distractions in the form of additional tasks or the environment as well as fatigue have a detrimental effect on BCI performance [11]. High temperatures may have had a detrimental effect on the outdoor performance of participants two, three and six. Nonetheless, an ideal BCI should function under any condition and BCIs should be evaluated under different environmental conditions outside of the laboratory. To deal with changes in the environment, adaptations to the signal processing used in the BCI may be necessary [12]. Additionally, the signal processing methods used in the current publication may benefit from being updated to the approaches outlines in e.g. in [13].

In its current form the mobile platform we used for the experiments is not well suited for BCI control. Sometimes commands were not executed, in particular if there was a slight slope, which had a frustrating effect on the participants. There may have also been an effect of friction as sometimes the steering angle could not be set. It has to be considered that driving short distances of about one meter with low speeds is not optimal for the motor of the mobile platform.

CONCLUSION

We were able to show that low-cost EEG hardware can be used to control a mobile platform using tactile ERPs an a real world driving task. The mobile platform must be adapted to react precisely to the discrete commands issued with a ERP BCI. Environmental influences are a key component for this type of experiment. Even if they have a negative impact on the performance of the BCI should only be protected against to the extent as not to cause any discomfort for the user. To summarize, we were able to show that BCI control of the mobile platform with tactile stimulation is possible and important steps for future research were determined.

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