Continuous Brain-Actuated Control of an Intelligent Wheelchair by Human EEG

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Abstract

The objective of this study is to assess the feasibility of controlling an asynchronous and non-invasive brain-actuated wheelchair by human EEG. Three subjects were asked to mentally drive the wheelchair to 3 target locations using 3 mental commands. These mental commands were respectively associated with the three wheelchair steering behaviors: *turn left*, *turn right*, and *move forward*. The subjects participated in 30 randomized trials (10 trials per target). The performance was assessed in terms of percentage of reached targets calculated in function of the distance between the final wheelchair position and the target at each trial. To assess the brain-actuated control achieved by the subjects, their performances were compared with the performance achieved by a random BCI. The subjects drove the wheelchair closer than 1 meter from the target in 20%, 37%, and 7% of the trials, and closer than 2 meters in 37%, 53%, and 27% of the trials, respectively. The random BCI drove it closer than 1 and 2 meters in 0% and 13% of the trials, respectively. The results show that the subjects could achieve a significant level of mental control, even if far from optimal, to drive an intelligent wheelchair, thus demonstrating the feasibility of continuously controlling complex robotics devices using an asynchronous and non-invasive BCI.

1 Introduction

Brain-computer interfaces (BCI) research aims at operating mentally a variety of devices [1, 2, 3, 4, 5, 6, 7]. Our work is focused on developing asynchronous and non-invasive EEG-based brain-computer interfaces for continuous control of robots and wheelchairs [6, 8]. These BCI systems allow users to control such robotics devices spontaneously, at their own pace without needing any external cue that drives the interaction. To do so the users learn to voluntary modulate EEG oscillatory rhythms by executing different mental tasks (i.e., mental imagery) that are associated to different steering commands. We facilitate this learning process selecting those stable user-specific EEG features that maximize the separability between the EEG patterns associated to each mental task. Furthermore, we implement shared control techniques between the BCI and the intelligent wheelchair to assist the subject in the driving task [9, 10]. This paper describes one experiment that shows the feasibility of mentally controlling an intelligent wheelchair.

2 Methods

2.1 EEG Data Acquisition

Data was recorded with a portable Biosemi acquisition system using 64 channels sampled at 512Hz and high-pass filtered at 1Hz. Then, the signal was spatially filtered using a common

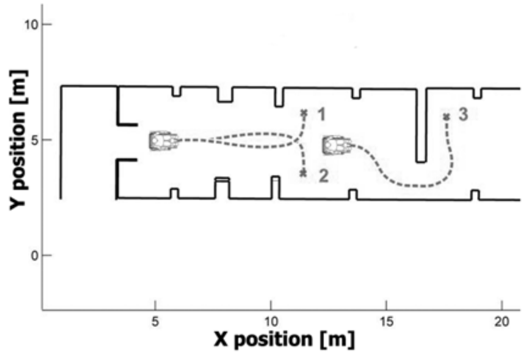

Figure 1: Indoor environment utilized in the experimental task. The subjects were asked to drive the wheelchair to targets 1, 2 and 3. The figure also depicts the initial positions and ideal trajectories for each target. X and Y axis in meters.

average reference (CAR) before estimating the power spectral density (PSD) in the band 8-46 Hz with 2 Hz resolution over the last 1 second. The PSD was estimated every 62.5 ms (i.e., 16 times per second) using the Welch method with 5 overlapped (25%) Hanning windows of 500 ms. Thus, an EEG sample was a 1344-dimensional vector (64 channels times 21 frequency components).

Obviously, not all these 1344 features are used as control signals. Section 2.3 describes the algorithms to estimate the relevance of the features for discriminating the mental commands and the procedure to select the most stable discriminant features that are fed to the classifier embedded in the BCI. This classifier processes each of the EEG samples and the BCI combines 8 consecutive responses to deliver a mental command every 0.5 seconds.

2.2 Experimental Task and Analysis

Three subjects were asked to mentally drive the wheelchair to reach 3 target locations while avoiding obstacles (see Fig. 1). Reaching a target is a more complex task than simply navigating. This experiment is more challenging in a second respect, namely subjects cannot manoeuver back the wheelchair if they overshot the target by more than 2 meters, thus missing the correct turn. If this is the case, the trial was considered a failure. The motivation for this experiment is to assess how well naive (or almost naive) subjects can mentally drive the wheelchair along "almost" optimal trajectories. To measure the performance of our brain-actuated wheelchair we have compared the final position of the wheelchair with the end point of the desired trajectory. In particular, we have calculated the percentage of reached targets as a function of the distance between the final wheelchair position and the target at each trial. Furthermore, to assess the degree of mental control achieved by the subjects, their performances were compared with that of a random BCI utilized as a baseline—i.e., the wheelchair was driven by such a random BCI.

Subject 1 had previous experience in mentally driving in simulated environments but no experience driving the wheelchair, subject 2 had previous experience in mentally driving the simulated and real wheelchair (3 days). Subject 3 did not have any previous driving experience. Each subject, and the random BCI, participated in 30 randomized trials (10 trials per target). To drive the wheelchair, subjects 1 and 2 utilized the following three mental commands: imagination of a left hand movement, words associations and rest. These mental commands were respectively associated with the three wheelchair steering behaviors: *turn left*, *turn right* and *move forward*. Subject 3 utilized different mental commands: words associations, arithmetic operations and rest, associated with the aforementioned steering behaviors, respectively.

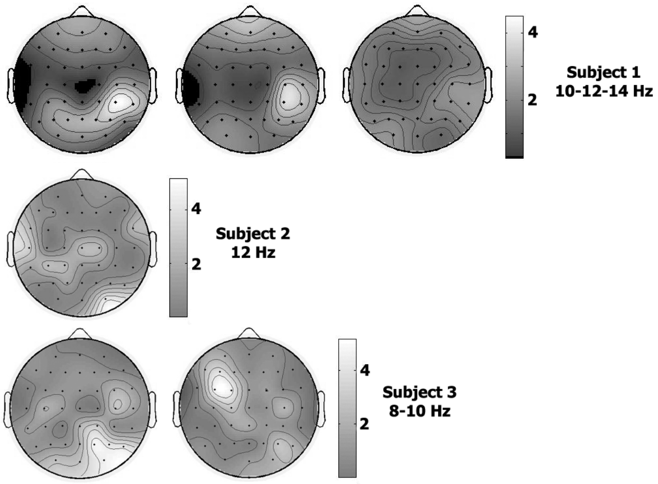

Figure 2: Electrode contribution in % for each selected frequency component for each subject.

2.3 Calibration Sessions and EEG Feature Extraction

The three subjects participated in 20 calibration sessions utilized to extract subject specific stable discriminant EEG features and build a BCI classifier (statistical Gaussian classifier, see [6] for details) for each subject. In these sessions, the subjects sat in a chair looking at a fixation point placed in the center of a monitor. The subjects were asked to execute the three mental tasks in a counterbalanced order informing the operator when they started executing the task. Each calibration session was integrated by 6 trials each, 2 trials per class. Each trial lasted for 7 seconds but only the last 6 were utilized in the analysis to avoid preparation periods where the subjects were not yet engaged in the execution of the mental task. During these sessions the subjects did not received any feedback.

The feature extraction procedure was the same than that utilized in other experiments involving a simulated wheelchair [8]. The data from the 20 calibration sessions were grouped in 4 blocks (B1, B2, B3 and B4) of 5 consecutive sessions. Taking into account the recordings timing, we built different configurations of training and testing sets (train-test): B1–B2, B1–B3, B1–B4, B2–B3, B2–B4, B3–B4, (B1+B2)–B3, (B1+B2)–B4, (B1+B2+B3)–B4. Feature extraction was done in a sequential way, where we first pick stable frequency components and then chose the best electrodes. To assess the stability of the frequency components we applied 21 canonical variates analysis (CVA) [11], one per frequency component, on the training set of each configuration. For each canonical space we ranked the electrodes according to their contribution to this space. Then, we built up to 15 LDA classifiers, each using those electrodes that contributed more than c%, with $c \in \{1.0, 2.0, ..., 15.0\}$ (see [11] for more details). We used the stability of the classifier accuracy over the different configurations to select the frequency components. In particular, we selected those frequencies that performed systematically among the top 5. Afterwards, for each selected frequency, we took the configuration of electrodes (out of the 15 possible ones) that yielded the highest classification accuracy on the configuration (B1+B2+B3)–B4. Finally, we tested the different combinations of selected frequencies (with their associated electrodes) on the configuration (B1+B2+B3)–B4 and chose the best one. At the end of this sequential process the selected frequencies were $\{10, 12, 14\}$ Hz for subject 1, $\{12\}$ Hz for subject 2, and $\{8, 10\}$ Hz for subject 3. Fig. 2 depicts the electrodes contribution, for each selected frequency component for each subject. Finally, we built the statistical Gaussian classifier for each subject using their individual selected features from all the data of the calibration sessions. The reasons for using a LDA classifier for feature extraction rather than the final Gaussian classifier were the simplicity and speed of training of the former. Furthermore, LDA is a special case of our Gaussian classifier.

2.4 EEG features and EOG/EMG Offline Analysis

To assess weather the experimental subjects were using eye movements or muscular activity components embedded in the EEG as control signals, electromyogram (EMG) was recorded from subjects 1 and 2 (subjects that executed imagination of left hand movement to *turn left*). Bipolar EMG was recorded using 2 surface electrodes placed on the forearm muscle Extensor Digitorum. Bipolar electrooculogram (EOG) was measured from the three subjects using 2 surface electrodes placed below and laterally to the left eye respectively. The PSD was estimated for EMG and EOG using the same procedure as for EEG (see Sect. 2.1).

If there were EMG and EOG components embedded in the EEG utilized as control signals, these components would not be equiprobably distributed over the mental commands recognized by the BCI (i.e., the embedded statistical Gaussian classifier). To visually explore how they were distributed, the 21 frequency components estimated from EMG and EOG of each subject (only EOG in the case of subject 3) were utilized to built a canonical space (utilizing all samples from the 30 trials) according to the mental commands recognized by the BCI. Then all the samples were projected in the canonical space. Finally, an LDA classifier was applied to assess the separability of the mental commands. Fig. 3 shows the canonical space for each subject built using both the EEG features utilized as control signals (left column) as well as the EOG and EMG frequency components (right column). As expected, the mental commands distributions recognized by the statistical Gaussian classifier are highly separable in the canonical space when it is built with the EEG features (see Figure 3, *Left*). This is reflected by the LDA classification accuracies: 76.34%, 71.81% and 76.50% for subjects 1, 2 and 3, respectively. However, the mental commands distributions are not separable when the canonical space is built with the EOG and EMG frequency components (see Figure 3, *Right*), what means that they are uniformly distributed among the mental commands. In this case, the LDA classification accuracies are close to chance level: 41.08%, 38.04% and 35.75%, for subjects 1, 2 and 3, respectively. All together, these results show that the experimental subjects did not utilize eye movements or muscular activity components embedded in the EEG as control signals.

3 Results

Fig. 4 shows the percentage of targets reached by each subject and the random BCI as a function of the distance between the final wheelchair position and the target at each trial. The results reflect the importance of previous experience in order to successfully drive the wheelchair. Subject 2, who had previous driving experience with both the simulated and the real wheelchair, brought it closer to the targets. On the contrary, subject 3, who did not have any previous driving experience, had more difficulties to place the wheelchair close to the targets. Subject 1, who had only previous experience in simulation, achieved an intermediate performance.

Despite the different driving performances among subjects, the three of them showed a significant degree of mental control of the wheelchair, which requires rather fast and accurate decisions. For instance, to drive the wheelchair to target 3, the most difficult one, the subject needs to pass through of the narrow passage in the opposite direction, right, and then immediately make a sharp turn to the left. It's also worth noting that the subjects missed quite a few times targets 1 and 2 because they tried to reach them following a straight line and the collision avoidance behavior of the wheelchair (for details see [9, 10]) pushed the wheelchair away from the target. As shown in fig. 1, the optimal trajectory is not straight, but the subjects needed some time to learn appropriate driving strategies compatible with the behavior of the intelligent wheelchair.

To measure the degree of mental control exhibited by the subjects, and to show the complexity of the task, we run an experiment where the wheelchair was driven by a random BCI (i.e., the mental steering command—left, right, or forward—was selected randomly every 0.5 seconds). The performance of such a random BCI was such that it never brought the wheelchair closer than 1 meter from the target whereas subjects 1, 2 and 3 did it in 20%, 37% and 7% of the trials, respectively. The subjects' level of mental control is even higher when we consider the percentage

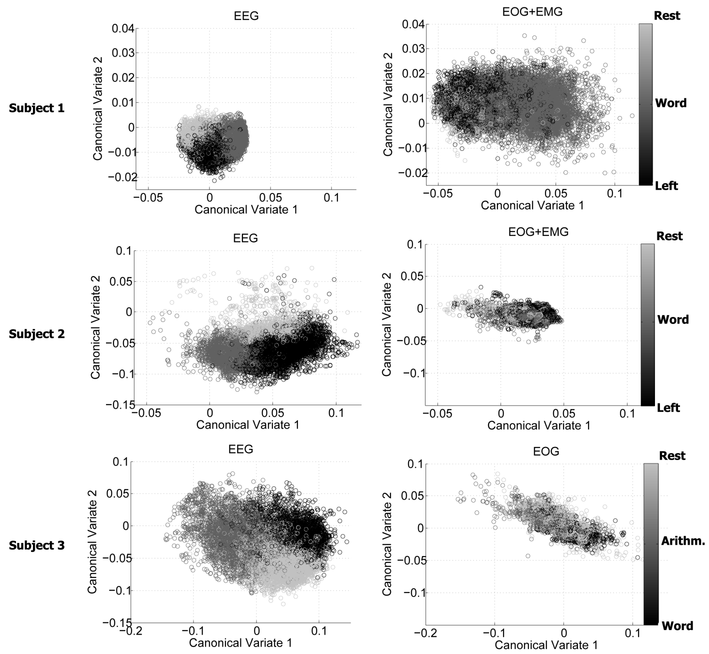

Figure 3: *Left*: canonical spaces built using the EEG features utilized as control signals. *Right*: canonical spaces built using the EOG+EMG (subjects 1 and 2) or EOG (subject 3) frequency components. All canonical spaces built according to the mental commands recognized by the BCI (statistical Gaussian) classifier.

of trials where the wheelchair was driven closer than 2 meters from the target. In this case, subjects 1, 2 and 3 achieved the task in 37%, 53% and 27% of the trials, whereas the random BCI did it only in 13% of the trials.

4 Conclusions

The results of this experiment show that subjects can operate our asynchronous EEG-based BCI to control a wheelchair, task that requires rather fast and accurate decisions. Also, they can autonomously operate the BCI without the need for adaptive algorithms externally tuned by a human operator to minimize the impact of EEG non-stationarities. However, the performances seem to be lower than the obtained with the simulated version of the wheelchair [8]. Moreover, subjects 1 and 2, who had previous experience with the simulated wheelchair, report that it is more difficult to drive the real wheelchair because of its more complex behavior. Nevertheless, it is worth noting that the performance of the subjects, even the naive subject, is significantly better than a random BCI. This proves that the intelligent wheelchair cannot achieve the task by itself, but requires appropriate mental commands delivered by the subject at the right times.

In summary, these results show that subjects can rapidly achieve a significant level of mental control, even if far from optimal, to drive an intelligent wheelchair, thus demonstrating the feasibility of continuously controlling complex robotics devices using an asynchronous and non-invasive EEG-based BCI.

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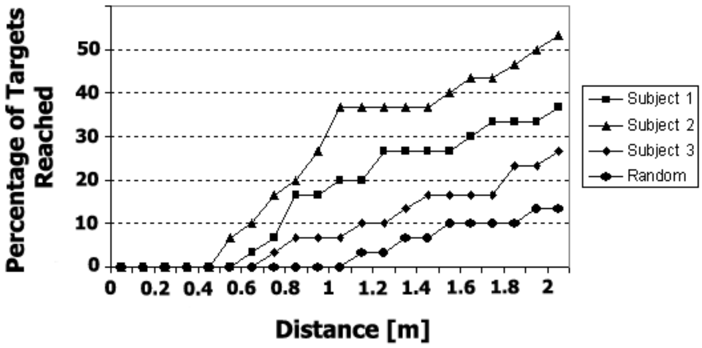

Figure 4: Percentage of reached targets by each subject and the random BCI as a function of the distance between the final wheelchair position and the target (distance in meters).

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