NON-INVASIVE BRAIN COMPUTER INTERFACE FOR MENTAL CONTROL OF A SIMULATED WHEELCHAIR

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SUMMARY: This poster presents results obtained from experiments of driving a brain-actuated simulated wheelchair that incorporates the shared-control intelligence method. The simulated wheelchair is controlled offline using band power features. The task is to drive the wheelchair along a corridor avoiding two obstacles. We have analyzed data from 4 naïve subjects during 25 sessions carried out in two days. To measure the performance of the brain-actuated wheelchair we have compared the final position of the wheelchair with the end point of the desired trajectory. The experiments show that the incorporation of a higher intelligence level in the control device significantly helps the subject to drive the robot device.

INTRODUCTION

Recent experiments have shown the possibility of using the brain electrical activity to directly control the movement of robots or prosthetic devices in real time [1]. In order to provide a more practical environment for the subject to use the BCI for control, there is a need to have an adaptive shared autonomy between two intelligent agents—the human user and the robot—so that the user only conveys intents that the robot performs autonomously [2]. Although the initial brain-actuated robot had already some form of cooperative control, shared autonomy is a more principled and flexible framework.

METHODS

In this paper, the experiment protocol is similar to that described in [3]. In order to control the simulated wheelchair, the classifier embedded in the BCI is fed with the power of the frequency band 8-14 Hz from 10 scalp EEG electrodes and it sent its output every 0.5 s to the robot. The simulated wheelchair has two levels of intelligence, namely A0 (it allows the wheelchair to detect obstacles and stop before colliding) and A1 (it detects obstacles and avoids them).
The task is to drive the wheelchair along a corridor avoiding two obstacles (Figure 1). We have analyzed data from 4 naïve subjects during 25 sessions carried out in two days. The classifier embedded in the BCI was trained with data from 5 consecutive sessions and tested over the next 5 consecutive sessions. To measure the performance of the brain-actuated wheelchair we have compared the final position of the wheelchair with the end point of the desired trajectory.

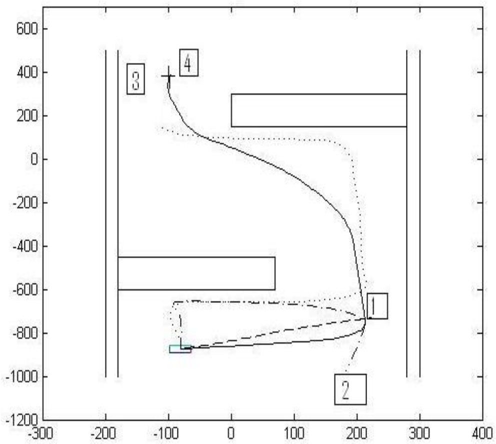

Figure 1: Example of trajectories in the simulated environment. The starting point for the wheelchair is at the bottom left in front of the obstacle. The axes give the coordinates of the simulated environment in cm.

RESULTS

Figure 1 shows a few trajectories obtained from the experiments. Using intelligence level A0, most of the time, the wheelchair stops moving whenever it comes across any obstacles, causing it to stay near the starting point as in the dashed line path (labeled 1) in Figure 1. The solid line (labeled 4) is the desired trajectory and the end point of this trajectory is used as a reference for comparison with other end points reached by the brain-actuated wheelchair for each session and subject. The dotted line (labeled 3) is an example of a trajectory reaching the target. Distance from starting point to the target is 1262 cm. The dotted-dash line (labeled 2) shows the wheelchair turning to the opposite direction further away from the starting point. If the simulated wheelchair ends within 50 cm from the target, it is considered the task has been achieved.
Results for the 4 subjects are tested with the simulator using intelligence level A1 as shown in the graphs of

Figure 2 to 5. In these figures, distances of more than 1262 cm correspond to trajectories where the subject sent a series of wrong mental commands at the beginning and the wheelchair turned away from the target as in the case of trajectory 2 in Figure 1.
Figure 6 shows the comparison between trajectories generated with online learning [4] and without online learning for Subject 1.

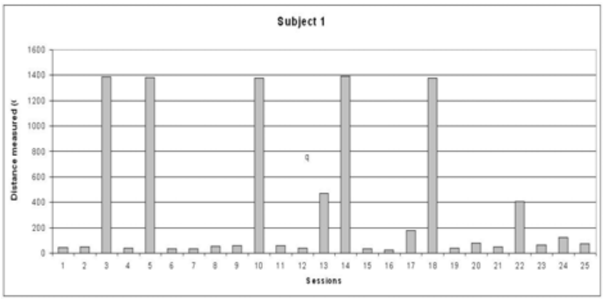

Figure 2: Subject 1 hits the target in 16 out of 25 sessions with an average distance to target of 355 cm.

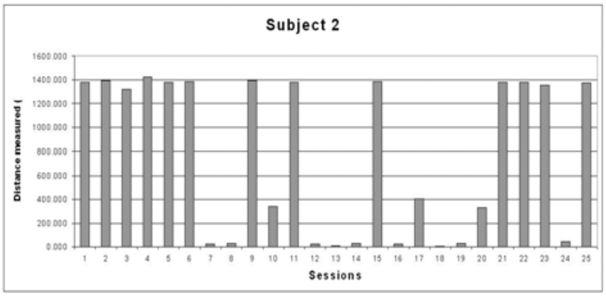

Figure 3: Subject 2 hits the target in 9 out of 25 sessions with an average distance to target of 769 cm.

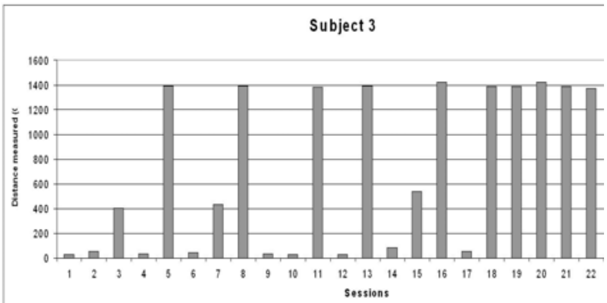

Figure 4: Subject 3 hits the target in 10 out of 25 sessions with an average distance to target of 740 cm.

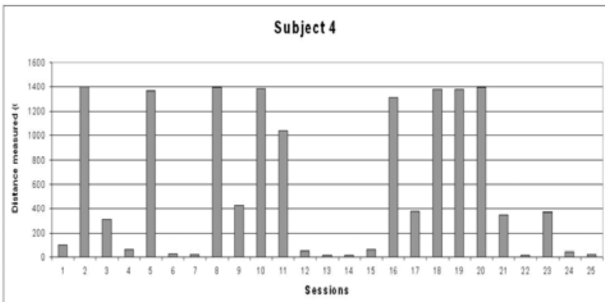

Figure 5: Subject 4 hits the target in 11 out of 25 sessions with an average distance to target of 573 cm.

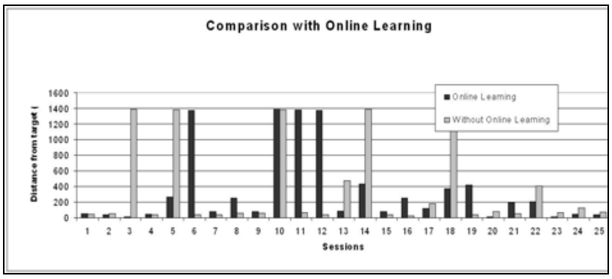

Figure 6: Comparison of online learning results with data without online learning for Subject 1. Average distance to target for online learning is 344 cm.

DISCUSSION

Despite the fact that the subjects' performance are quite far from optimal—because among other reason, they are novel— the results show that the incorporation of shared autonomy with A1 intelligence level allows subjects to achieve the task a considerable number of times. This is not the case when the simulated wheelchair has only A0 intelligence level, when the target is never reached. It is also worth noting that the performance of Subject 1 and Subject 4 increased at the last few sessions while Subject 3 performs best in the beginning of the sessions and Subject 2 is able to reach the target more frequent in the middle of the sessions. Finally, as expected, the incorporation of online learning [4], improves the performance.

CONCLUSION

This paper shows the importance of having a higher intelligence level in the wheelchair (or control device) to help the subject achieve the task with a high probability from the very first trial, although performance between subjects varies across sessions. For future work, we plan to estimate the subject's intention using a probabilistic framework, as in [2], and to incorporate learning capabilities in the robot controller to improve the entire brain-actuated device.

REFERENCES

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