The role of shared-control in BCI-based telepresence

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***Abstract*—This paper discusses and evaluates the role of shared control approach in a BCI-based telepresence framework. Driving a mobile device by using human brain signals might improve the quality of life of people suffering from severely physical disabilities. By means of a bidirectional audio/video connection to a robot, the BCI user is able to interact actively with relatives and friends located in different rooms. However, the control of robots through an uncertain channel as a BCI may be complicated and exhaustive. Shared control can facilitate the operation of brain-controlled telepresence robots, as demonstrated by the experimental results reported here. In fact, it allows all subjects to complete a rather complex task, driving the robot in a natural environment along a path with several targets and obstacles, in shorter times and with less number of mental commands.**

***Index Terms*—Brain–Computer Interface (BCI), EEG, Shared control, Telepresence, Mobile robot.**

I. INTRODUCTION

The capability to use brain signals as a new communication and control channel, so-called brain-computer interface (BCI), is a key point in the assistive technology field. In this respect, the last years have seen an increased in sophistication BCI-driven applications. In this work we want to explore a BCI-controlled mobile device for *telepresence*. Such a telepresence mobile robot enables patients, constrained to remain in bed because of their severe degree of paralysis, to join relatives and friends to participate in their activities. Alternatively, it can also help able-bodied users (such as astronauts [1], [2]) in the case of 'situational disability' situations where their hands are busy or inadequate.

In this framework, the main question is how the subject might drive a mobile device by means of an uncertain channel such as a BCI. An answer to this fundamental issue is the well-known shared control approach [3], [4], [5], [6]. The cooperation between a human and an intelligent device allows the subject to focus the attention on his final destination and ignore low level problems related to the navigation task (i.e., obstacle avoidance). Researchers have explored two general approaches to shared control, namely autonomous and semi-autonomous. In the former, the subject interacts with the robot just by indicating the final destination and the robot decides the best trajectory to reach it. Examples of such an approach are museum tour-guide robots [7] and some BCI-controlled wheelchairs [8]. Disabled people, however, prefer to keep as much as control as possible. Thus, for them, a *semi-autonomous* approach is more suitable for a BCI-controlled telepresence robot, where the intelligent system helps the human user to cope with problematic situations such as obstacle detection and avoidance [9]. Such a semi-autonomous framework has been largely explored for assistive wheelchairs [4], [10], including brain-controlled wheelchairs [11], [12], [13], [14].

Since our goal is to develop BCI systems for physically-disabled people, we follow this semi-autonomous approach to give BCI users the feeling of full control of the robot. Furthermore, in this paper we perform a quantitative evaluation of the benefit of shared control for a BCI robot. The experimental setup for this BCI-based telepresence application is a natural environment (including people moving around), thus replicating a daily life situation where the patient might want to drive the mobile robot to different rooms of their apartment.

In the following sections we will describe our BCI system, the mobile robot and our shared control implementation. Then, we will present the experimental setup and the results achieved.

II. BCI SYSTEM

To drive our telepresence robot, subjects use an asynchronous spontaneous BCI where mental commands are delivered at any moment without the need for any external stimulation and/or cue [15], [16]. To do so the users learn to voluntary modulate EEG oscillatory rhythms by executing two motor imagery tasks (i.e., imagination of movements such as either right hand vs. left hand, or feet vs. left hand). Each of these mental tasks is associated to a steering command, either *right* or *left*. Interestingly, if no mental command is delivered, the robot moves forward thus implicitly executing a third driving command.

For our experiments, EEG was recorded with a portable 16-channel g.tec system at 512 Hz and band-pass filtered between 0.1 Hz and 100 Hz. Each channel was then spatially filtered with a Laplacian derivation before estimating its power spectral density (PSD) in the band 4-48 Hz with 2 Hz resolution over the last second. The PSD was computed every 62.5 ms (i.e., 16 times per second) using the Welch method with 5 overlapped (25%) Hanning windows of 500 ms.

The input to the classifier embedded in the BCI is a subset of those features (16 channels x 23 frequencies). We use the algorithm described in [13] to estimate the relevance of the features for discriminating the mental commands delivered to the robot. This algorithm is run on EEG data recorded during several training sessions separately (3 sessions for the experiments reported here) and we then select the features with discriminant values consistently high in all sessions.

The classifier is a statistical Gaussian classifier that computes the probability distribution over the mental commands of an EEG sample [15]. The BCI integrates over time the outputs of the classifier until it accumulates enough evidence about the user's mental intent using Eq. 1:

$$p(y_t) = \alpha \times p(y_t|x_t) + (1-\alpha) \times p(y_{t-1}) \qquad (1)$$

where $p(y_t|x_t)$ is the probability distribution, $p(y_{t-1})$ the previous distribution and α the integration parameter. That is, probabilities are integrated until a class reaches a certainty threshold about the subject's intent to change the robot's direction. At this moment the mental command is delivered and the probabilities are reset to uniform distribution.

III. Telepresence Robot

Our telepresence robot is Robotino™ by FESTO, a small circular mobile platform (diameter 38 cm, height 23 cm) with three holonomic wheels (Fig. 1). It is equipped with nine infrared sensors capable to detect obstacles up to ∼15 cm (depending on light condition) and a webcam that can also be used for obstacle detection, although for the experiments reported in this paper we only rely on the infrared sensors. For telepresence purposes, we have added a notebook with an integrated camera: the BCI user can see the environment through the notebook camera and can be seen by others in the notebook screen. The video/audio communication between the telepresence robot and the subject's PC is done by means of commercial VoIP (Skype). This configuration allows the BCI user to interact remotely with people.

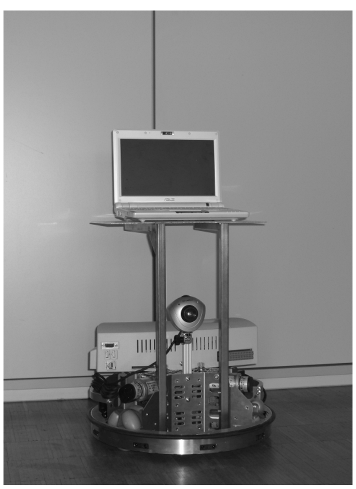

Fig. 1. The telepresence robot.

IV. Shared Control

Our implementation of shared control focuses on low-level obstacle detection and avoidance and doesn't give the robot the capability to decide autonomously the direction of travel. This way the subject keeps full control of the driving of the robot. For the sake of safety, the robot stops automatically in the case it looses the network connection with the BCI.

The default behavior of the robot is to move *forward* at a constant speed. Then, upon the reception of a mental command it turns *left* or *right* by 30 degrees. To avoid obstacle collision, the robot uses its three frontal infrared sensors (Fig. 2). Without shared control, the robot stops in front of the detected obstacle and wait for the next mental command. If shared control is enabled, the obstacle avoidance module will make the robot turns towards the opposite direction where the obstacle is detected until the path is free. In the case there are two simultaneous commands, one from the subject and the other from the obstacle avoidance module, the latter has the priority. In any other case, any arriving command interrupts the current action the robot is executing.

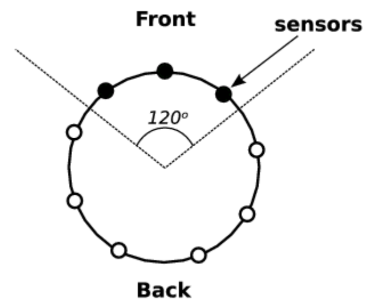

Fig. 2. Schema of the position of the infrared sensors on the robot. The three frontal sensors have been enabled for this experiment.

V. Subjects and Methods

Four healthy volunteers participated in our experiments (males, age 27 ± 0.8). Although the subjects were already trained in BCI, they didn't have any experience with the mobile robot. In addition, subjects 1 and 4 were BCI beginners. Unfortunately, subject 4 could not finish all the experiments.

The experimental environment was a natural working space with different rooms and corridors (Fig. 3). The subject was seated at position *S*, the robot started from position *R*, and there were four target positions *T1*, *T2*, *T3*, *T4*. The subject's task was to drive the robot along one of three possible paths *P1*, *P2*, *P3*, each consisting of two targets and driving back to the start position. The experimental space contains *natural* obstacles (i.e., desks, chairs, furniture, and people) and six additional objects in the middle of the paths (small squares with a circle).

During a trial, the subject needed to drive the robot along one of the paths. Subjects were asked to perform the task as fast as possible. A trial was considered successful if the robot travelled to the two target positions and back to the start position within a limited amount of time (12 min).

Since the goal of this work was to evaluate the contribution of shared control for a BCI telepresence robot, the experiment was run under four conditions: with or without shared control in combination with BCI or manual control. In the case of manual control the subject drove the robot by delivering manual commands through a keyboard (left, right arrows) and travelled each path once. In the case of BCI control the subjects drove the robot along each path twice (in pseudorandom order).

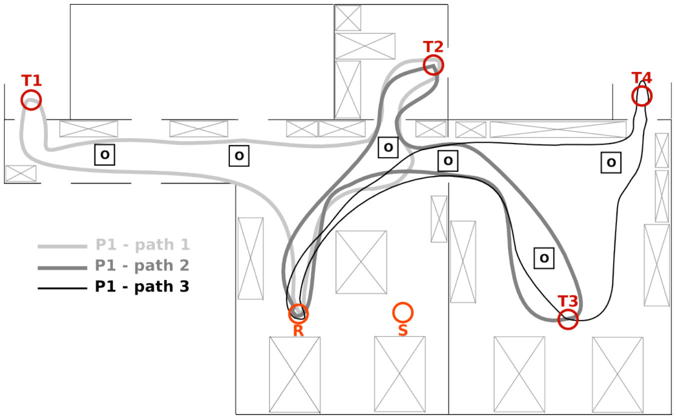

Fig. 3. The experimental environment. The figure shows the four target positions (*T1*, *T2*, *T3*, *T4*), the robot start position (*R*) and the subject's position (*S*). Lines *P1*, *P2*, *P3* indicate the three possible paths. Additional obstacles (*Os*) are in the middle of the paths.

For each trial we recorded the total time, the number of commands sent by the user (manual or mental), and the number of commands delivered by the obstacle avoidance module (in the shared control condition). Table I lists the experimental parameters and their values.

TABLE I
EXPERIMENTAL PARAMETERS

Number of control commands	2
Number of targets per path	2
Number of paths	3
Number of conditions	4
Number of trials per path under manual control	1
Number of trials per path under BCI control	2
Total number of trials	18
Timeout	12 min

VI. RESULTS

The first striking result of our experiments is that all subjects succeeded in all the trials for all conditions. Regarding the incorporation of shared control, it boosted the performance for both manual and BCI control in all trials for all subjects. Figure 4 shows the time needed for the four subjects to drive the robot along the three paths. Even in the case of manual control (first two bars in the graphs), shared control reduced the time to perform the task: subject 1, 12.7±8.6%; subject 2, 4.6±2.1%; subject 3, 10.9±8.8%; subject 4, 4.9±2.9%. The benefit of shared control becomes more evident when subjects drove the robot mentally (last two bars in the graphs): subject 1, 40.2±9.2%; subject 2, 12.0±9.1%; subject 3, 39.3±8.1%.

But the most important result of our experiments is that shared control allowed all the subjects to drive mentally the telepresence robot almost as fast as when they did the task delivering manual control without shared control. The ratio of the average time for all paths of BCI (with shared control) vs. manual control (without shared control) is: subject 1, 1.22; subject 2, 1.11; subject 3, 1.08.

Shared control also helped subjects in reducing the cognitive workload as measured by the number of commands (manual or mental) they needed to deliver to achieve the task (Fig. 5). In the case of mental control, shared control led to significant decreases (last two bars in the graphs): subject 1, 51.6±6.4%; subject 2, 19.5±15.3%; subject 3, 27.7±11.1%.

Another way to look at the benefit of shared control for the telepresence robot is to measure the number of commands (mental or manual) and the time to reach each of the three targets of the paths. Figures 6 and 7 report those performances for the case of manual and mental control, respectively. Results have been averaged across all subjects. Particularly in the case of mental control we can see a high correlation between the number of commands delivered by the subjects without or with shared control (first two bars in the upper graphs of Figures 6 and 7) and the time needed to reach a target. For all targets we observe the same general trend: shared control allowed the subjects to deliver significantly less commands and reach the target faster. For completeness, the figures also include the number of autonomous commands taken by the robot to reach the targets, which were always significantly less than the mental commands delivered by the subjects.

We also observed that, to drive a brain-controlled robot, subjects do not only need to have a rather good BCI performance, but they also need to be fast in delivering the appropriate mental command at the correct time —otherwise they will miss key maneuvers to achieve the task efficiently (e.g., turning to pass a doorway or enter a corridor). In our experience, fast decision making is critical and it depends on the proficiency of the subject as well as on his/her attention level.

VII. CONCLUSIONS

The experimental results reported in this paper demonstrate the benefits of shared control for brain-controlled telepresence robots. Despite that our shared control implementation only deals with low-level obstacle detection and avoidance, it allows all subjects to complete a rather complex task in shorter times and with less number of mental commands. Thus, we argue that shared control reduces subjects' cognitive workload as it: *(i)* assists them in coping with low-level navigation issues (such as obstacle avoidance) and *(ii)* helps BCI users to keep attention for longer periods of time, resulting in delivering fast commands.

Shared control is definitely useful for novel BCI subjects (i.e., subject 1), but even well-trained subjects benefit from it (i.e., subject 2). Interestingly, an experienced BCI user such as subject 2 delivers a much higher number of mental commands than the other subjects. This apparent anomaly is actually reflecting a voluntary will to be in full control of the telepresence robot.

In this paper we have described one of the first implementations of a shared-control BCI telepresence robot that is related to our previous work with wheelchairs [11], [12], [13], [14]. In

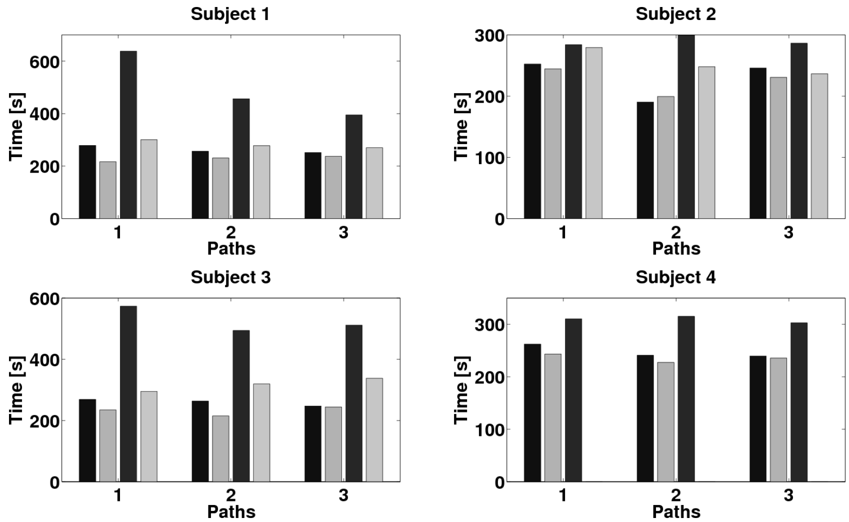

Fig. 4. Time to complete the task for the three paths. For each subject the bars show the results for the four conditions: no BCI - no shared control, no BCI - shared control, BCI - no shared control and BCI - shared control.

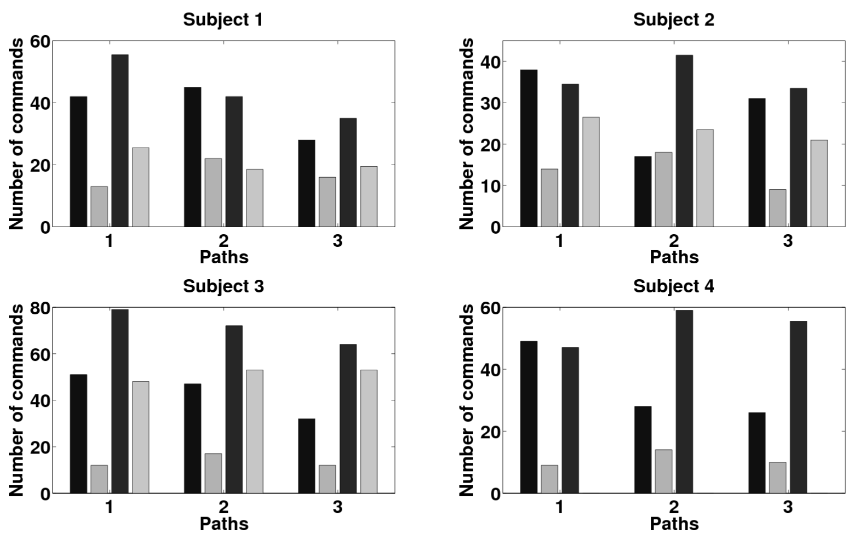

Fig. 5. Number of manual/BCI commands to complete the task for the three paths. For each subject the bars show the results for the four conditions: no BCI - no shared control, no BCI - shared control, BCI - no shared control and BCI - shared control.

the current paper, however, shared control only deals with low-level obstacle avoidance and it relies on very simple infrared sensors (as opposed to expensive laser range finders on the wheelchairs). The next implementation of shared control will incorporate simple vision modules for obstacle avoidance and recognition of natural targets (such as humans and tables) that will increase the operational range of the robot. Shared control will be also combined with our approach to support idle states so that users can deliver commands only when they wish to do so [17], thus enlarging subjects' telepresence experience.

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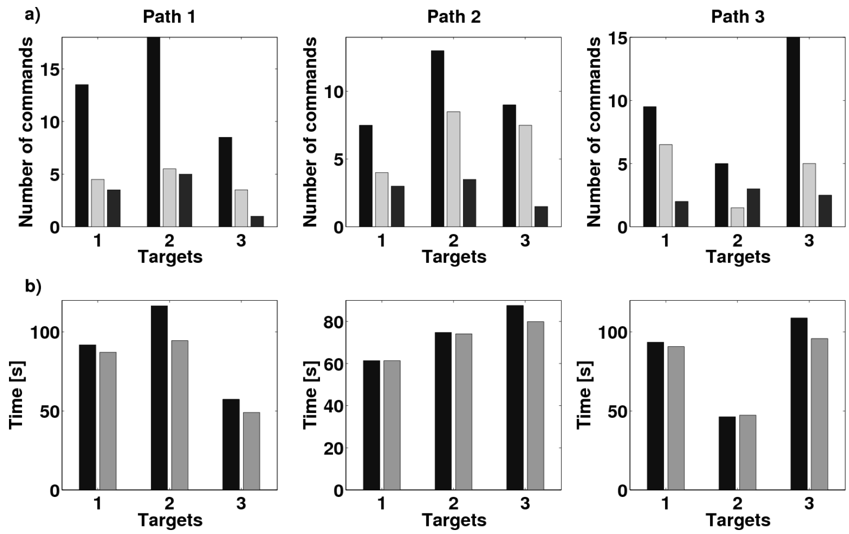

Fig. 6. Number of *manual* commands and time to reach the three targets of each path. *a)* Number of manual commands without shared control (first bar) and with shared control (second bar). The third bard gives the number of autonomous commands taken by the obstacle avoidance module when shared control is enabled. *b)* Time to reach the target without shared control (first bar) and with shared control (second bar).

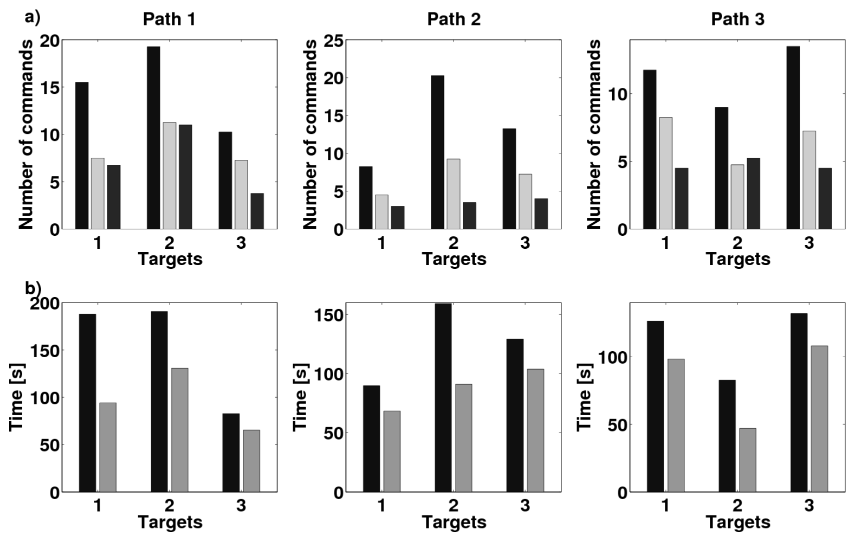

Fig. 7. Number of *mental* commands and time to reach the three targets of each path. Panels *a)* and *b)* as in Figure 6.

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