Human Brain-Teleoperated Robot between Remote Places

C. Escolano, J. Antelis and J. Minguez

Abstract— **This paper describes an EEG-based human brain-actuated robotic system, which allows performing navigation and visual exploration tasks between remote places via internet, using only brain activity. In operation, two teleoperation modes can be combined: robot navigation and camera exploration. In both modes, the user faces a real-time video captured by the robot camera merged with augmented reality items. In this representation, the user concentrates on a target area to navigate to or visually explore; then, a visual stimulation process elicits the neurological phenomenon that enables the brain-computer system to decode the intentions of the user. In the navigation mode, the target destination is transferred to the autonomous navigation system, which drives the robot to the desired place while avoiding collisions with the obstacles detected by the laser scanner. In the camera mode, the camera is aligned with the target area to perform an active visual exploration of the remote scenario. In June 2008, within the framework of the experimental methodology, five healthy subjects performed pre-established navigation and visual exploration tasks for one week between two cities separated by 260km. On the basis of the results, a technical evaluation of the device and its main functionalities is reported. The overall result is that all the subjects were able to successfully solve all the tasks reporting no failures, showing a high robustness of the system.**

I. Introduction

To command robots just by thought is a technical and social dream that is turning to be a reality due to the recent advances in brain-machine interaction and robotics. On one hand, brain-computer interfaces provide a new communication channel for patients with severe neuromuscular disabilities bypassing the normal output pathways, and also can be used by healthy users. On the other hand, robotics provides a physical entity embodied in a given space ready to perceive, explore, navigate and interact with the environment. Certainly, the combination of both areas opens a wide range of possibilities in terms of research and applications.

One of the major goals for human applications is to work with non-invasive methods (non intracraneal), where the most popular is the electroencephalogram (EEG). So far, systems based on human EEG's have been used to control a mouse on a screen [1], for communication such as a speller [2], an internet browser [3], etc. Regarding brain-actuated robots, the first control was demonstrated in 2004 [4], and since then, research has focused on wheelchairs [5], manipulators [6], small-size humanoids [7] and neuroprosthetics [8]. All these developments share an important property: the user and the robot are placed in the same environment.

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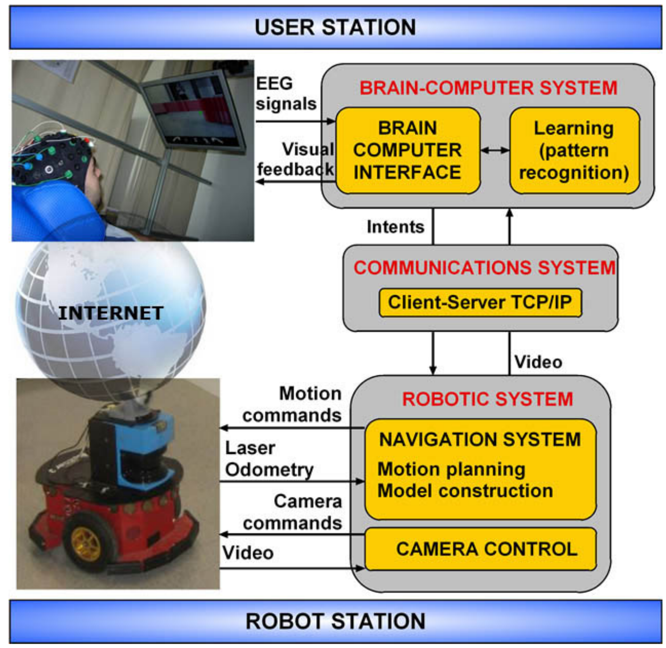


Fig. 1. Design of the brain-actuated teleoperation system: the two stations, the main systems, and the information flow among them.

A breakthrough in brain-teleoperated robots arose in January 2008, when a cooperation between two research teams enabled a monkey (located in the USA) to control the inferior part of a humanoid in Japan [9]. The animal was practiced a craniotomy; thus, the recording method to measure the brain activity was invasive. So far, there are no similar results in humans using non-invasive methods. Notice that the ability to brain-teleoperate robots in a remote scenario opens a new dimension of possibilities for patients with severe neuromuscular disabilities.

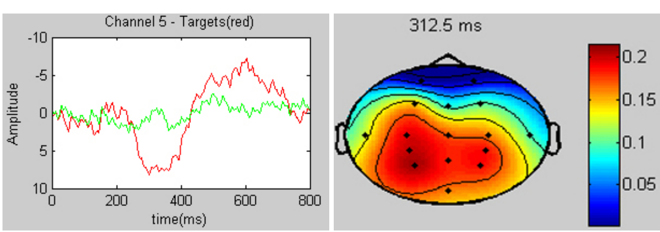
This paper reports the first EEG-based human brain-actuated teleoperation system, which allows the users to perform navigation and visual exploration tasks between remote places, using only their brain activity. This system relies on a user station and a robot station, both remotely located but connected via internet (Figure 1). In operation, two teleoperation modes can be combined: robot navigation and camera exploration. In both modes, the user faces a real-time video captured by the robot camera merged with augmented reality items, which is used as visual feedback for decision-making and process control. In this representation, the user concentrates on a target area to navigate to or visually explore; then, a visual stimulation process elicits the neurological phenomenon that enables the brain-computer system to decode the intentions of the user. In the navigation mode, the target destination is transferred to the autonomous navigation system, which drives the robot to the desired place while avoiding collisions with the obstacles detected by the laser scanner. In the camera mode, the camera is aligned with the target area to perform an active visual exploration of the remote scenario. This prototype has been validated using five healthy subjects in two consecutive steps: (i) screening plus training of the subjects, and (ii) pre-established navigation and visual exploration teleoperation tasks during one week between two laboratories located 260km apart. On the basis of the results, a technical evaluation of the device and its main functionalities is reported. The overall result is that all the subjects were able to successfully solve all the tasks reporting no failures, showing a high robustness of the system.

II. Brain-Computer System

This section describes the brain-computer system, which is located in the user's station (Figure 1).

A. Neuropsychological protocol and instrumentation

The neurophysiological protocol followed in this study is based on the P300 visually-evoked potential [10], which is usually measured in a human EEG. In this protocol, the user focuses his attention on one of the possible visual stimuli, and the BCI uses the EEG to infer the stimulus that the user is attending to. The P300 potential manifests itself as a positive deflection in voltage at a latency of roughly 300 msec in the EEG after the target stimulus is presented within a random sequence of non-target stimuli (Figure 2). The elicitation time and the amplitude of this potential are correlated with the fatigue of the user and with the saliency of the stimulus (in terms of color, contrast, brightness, duration, etc.) [10].



(a) (b)

Fig. 2. (a) Typical P300 response. The red line shows the EEG activity in one channel (elicited by the target stimulus), and the green line shows the activity for the non-target stimuli. (b) Topographical plot of the EEG distribution on the scalp at 300 msec. The area with more activity (mid-low part of the scalp) is the parietal lobe, where the P300 potential is elicited.

The BCI instrumentation consists of a commercial gTec EEG system (an EEG cap, 16 electrodes and a gUSBamp amplifier). The electrodes are located at FP1, FP2, F3, F4, T7, T8, C3, C2, C4, CP3, CP4, P3, P2, P4 and OZ, according to the international $10/20$ system as suggested in previous studies [11]. The ground electrode is positioned on the forehead (position Fz) and the reference electrode is placed on the left earlobe. The EEG is amplified, digitalized with a sampling frequency of 256Hz, power-line notch filtered and bandpass-filtered between 0.5 and 30Hz. The signal recording and processing as well as the graphical interface are developed with the BCI2000 platform [12], placed on an Intel Core2 Duo @ 2.10GHz with Windows XP OS.

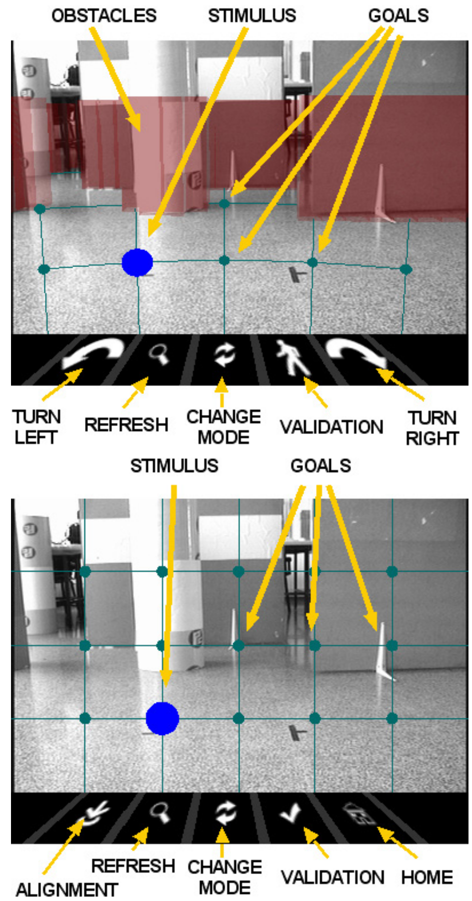


Fig. 3. (Upper section) Visual display in the robot navigation mode. (Lower section) Visual display in the camera control mode. In both figures an individual stimulus is shown; however, the real stimulation process is accomplished by means of rows and columns.

B. Graphical interface

The brain-computer system incorporates a graphical interface with two functionalities: (i) it visually displays a predefined set of options that the user can select to control the robotic system, and (ii) it develops the stimulation process to elicit the P300 visual-evoked potential and therefore, enables the pattern recognition system to decode the user's intents. Both functionalities are described next:

1) Visual display: The basis of the visual display is the live video received by the robot camera, which is used by the user as visual feedback for decision-making and process control. This video is augmented by overlapped items related to the two teleoperation modes: the robot navigation mode and the camera exploration mode.

The robot navigation mode allows the user to control the robot motion (Upper section of Figure 3). Overlapped to the video, the real environment obstacles are depicted by semitransparent walls. These walls are a 3D reconstruction built from the 2D map constructed in real-time by the autonomous navigation technology (section III). Furthermore, there is a 3D grid over the floor that maps the possible destinations that the operator can select to order the robot to reach the specific location. The possible destinations are at distances $(1.5m, 2.5m, 4m) \times (-20°, -10°, 0°, 10°, 20°)$. The obstacles hide the unreachable destinations of the grid. The icons in the lower part of the display represent the following options, from left to right: (i) turn the robot $45°$ left; (ii) refresh the live video to perform a selection based on a more recent visual information of the environment; (iii) change to the camera exploration mode; (iv) validate the previous selection; and (v) turn the robot $45°$ right.

The camera exploration mode allows the user to control the pan/tilt orientation of the robot camera to perform an active visual exploration of the environment (Lower section of Figure 3). Overlapped to the video, there is a 2D grid uniformly placed in the display that maps the possible locations that the operator can select to orientate the camera in that direction. The icons in the lower part represent the following options, from left to right: (i) align the robot with the horizontal camera orientation and change to the robot navigation mode; (ii) refresh the live video; (iii) change to the robot navigation mode; (iv) validate the previous selection; and (v) set the camera to its initial orientation.

2) Stimulation process: This process must elicit the P300 visual-evoked potential when the user is concentrated on a given option of the visual display. The options are "stimulated" by flashing a circle on a grid intersection or icon in the visual display. A sequence is a stimulation of all the options in random order as required by the P300 oddball paradigm. In order to reduce the magnitude of the posterior classification problem (subsection II-C) and the duration of a sequence, the Farwell & Donchin paradigm [13] was followed. Thus, the flashing of the stimulus is accomplished by means of rows and columns instead of flashing each option individually, obtaining 9 stimulations (4 rows plus 5 columns) per sequence. The topology of the augmented reality items is constant in both teleoperation modes to maintain a uniform stimulation pattern. All the elements of the display can be customized in terms of color, texture, shape, size and location; and all the scheduling of the stimulation process (time of exposition of each stimulus, inter-stimulus duration, inter-sequence duration and number of sequences) can be modified to equilibrate the user's capabilities and preferences with the performance of the system.

C. Pattern recognition strategy

Pattern recognition is a supervised learning module to recognize the P300 evoked potential, and thus, to infer the stimulus that the user is attending to in the stimulation process. The first step is to train the system via offline experiments, where the user faces the graphical interface with the stimuli described above. In this process, the user concentrates on a predefined sequence of selections that covers all the classes. The EEG is recorded and used to train the classification algorithm using a two-step supervised learning technique described next.

1) Feature extraction: The P300 signals are characterized in the time domain, so the information is in its waveform and latency times. Following [11], for each EEG channel 1 sec of samples are recorded after each stimulus onset. Then, these segments of data are filtered using the moving average technique, and decimated by a factor of 16. The resulting signals are plotted and the channels with the best P300 response are selected by visual inspection. Finally, the data segments of each channel are concatenated creating a single feature vector for the next stage.

2) Classification algorithm: In our system, the P300 signal is elicited for one of the four rows and the five columns during one sequence of the stimulation. Thus, there are two classification problems of 4 and 5 classes. For each problem, the StepWise Linear Discriminant Analysis (SWLDA) is used, extensively studied for P300 classification problems [11], and well-known for its good results obtained in online communication using visual stimulation. In our system, higher performances than 90% were achieved with SWLDA in less than an hour of training.

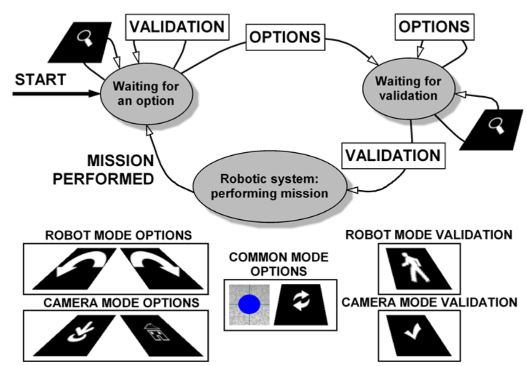


Fig. 4. Finite state machine that models the execution protocol.

D. Execution protocol

The users interact with the brain-computer system by means of its graphical interface according to the execution protocol, which is modeled by a finite state machine (Figure 4). Initially, the system starts in the navigation mode and in the state *Waiting for an option*. Then, the BCI develops a stimulation process, and if there are no errors in the pattern recognition, the option the user was concentrated on is selected (recall that there are different options according to the teleoperation mode). When the selected option is different than the refresh one (that simply refreshes the live video), the state turns to *Waiting for validation*. In this state, the BCI develops a stimulation process and a new option is selected. If the validation is selected, the last option is transferred to the robotic system and the state turns to *Robotic system: performing mission*; otherwise the stimulation process starts again until the validation is selected. In the state *Robotic system: performing mission*, the robot performs the relevant action (referred to as a mission) and meanwhile, the graphical interface displays live video captured by the robot camera and the BCI stops developing stimulation processes. Once the mission finishes, the robot remains waiting for another decision of the user, the video transfer stops (in order to perform the next stimulations over a static image), the BCI system receives an external flag coming from the robotic system and the state turns to *Waiting for an option*.

III. Robotic System

The robot is a commercial *Pioneer P3-DX* equipped with two computers. The low-level computer controls the back wheels that work in differential-drive mode and the high-level computer manages the rest of the computational tasks. The main sensor is a SICK planar laser placed on the frontal part of the vehicle. It operates at a frequency of 5Hz, with a 180° field of view and a 0.5° resolution (361 points). This sensor provides information about the obstacles located in front of the vehicle. The robot is also equipped with wheel encoders (odometry), with a wireless network interface card (to connect the vehicle to a local network during operation) and with a camera. The camera, placed on the laser, is a pan/tilt Canon VC-C4 with a $\pm 100^\circ$ pan field of view and a $+90^\circ / -30^\circ$ tilt field of view. The initial camera orientation (which is a customizable parameter) was set to 0° pan and -11.5° tilt, which provides a centered perspective of the environment starting roughly one meter in front of the robot.

The robot has been equipped with an autonomous navigation technology that drives the vehicle to the given destinations while also avoiding static and dynamic obstacles, detected by the laser sensor [14]. This module has two functionalities. On one hand, a modeling module integrates the sensor measurements to construct a local model of the environment and to track the vehicle location. We chose a binary occupancy grid map to model the static obstacles and the free space, and a set of extended Kalman filters to track the moving objects around the robot. We used a given technique [15] to correct the robot position, to update the map and to detect and track the moving objects around the robot. The static map travels centered in the robot. This map has a limited size, which is enough for presenting the required information to the user as described in the previous section and for computing the path so as to reach the selected goal. On the other hand, a local planner computes the local motion based on the hybrid combination of tactical planning and reactive collision avoidance. An efficient dynamic navigation function (D^*Lite planner [16]) was used to compute the tactical information (i.e. main direction of motion) required to avoid cyclic motions and trap situations. This function is well suited for unknown and dynamic scenarios because it works based on the changes in the model computed by the model builder. The final motion of the vehicle is computed using the ND technique [17], which uses a "divide and conquer" strategy based on situations and actions to simplify the collision avoidance problem. This technique has the distinct advantage of being able to cater to the complex navigational tasks such as maneuvering in the environment within constrained spaces (i.e. passage through a narrow doorway).

IV. Communications System and Integration

The communications system links the brain-computer system and the robotic system (Figure 5). It is composed of two clients (for the BCI and the robotic system) and a link server that concentrates the information flow and confers scalability to the system. All the connections among logical components are based on the client/server paradigm over TCP/IP.

The BCI client is multiplexed in time with the BCI system, with a period of roughly 30 msec and communicates with the link server through an internet connection. The robot client communicates with the link server by means of an *ad-hoc* wireless connection, encapsulating the autonomous navigation system as a thread, and synchronizing the orders to the camera and to the navigation system.

Regarding the information transfer, on one hand the navigation system transfers to the BCI the map model (400 bytes) and the robot location within the map (12 bytes). Furthermore, the images are captured by the camera with a resolution of 640x480 and are compressed in the *jpeg* standard format, obtaining an image size of approximately 30 kbytes (in our experiments 10 images per second were transferred). On the other hand, the BCI sends the goal location when it is computed (8 bytes). In execution, the upper boundary of the information transfer is close to 300 kbytes per second, adequate for the typical order of bandwidth of internet networks.

Regarding the time critical tasks in this integration, the robot motion controller is encapsulated in a dedicated computer (low-level computer) with a real-time operative system. The autonomous navigation system is encapsulated in another dedicated computer, and integrated into a task-based system to preserve the computation cycle. Both tasks communicate within a synchronous periodical task of 200 msec, where the navigation system reads from the client the goal location, the laser measurement, and requests the odometry to the low-level computer. Then, it executes the mapping and planning module and sends the translational and rotational velocity computed to the low-level computer.

V. Experimental Methodology

The objective of this study was to assess the performance and adaptability of the brain-actuated teleoperation system by able-bodied subjects in real settings. In the following subsections the recruitment of the participants for the study will be discussed, followed by a detailed account of the experimental protocol.

A. Participants

Participation recruitment for the study began after obtaining the protocol approval by the University of Zaragoza Institutional Review Board. Selection was made by the research team. A set of inclusion and exclusion criteria were applied for the recruitment of subjects in order to draw conclusions for the study over a homogeneous population. The inclusion

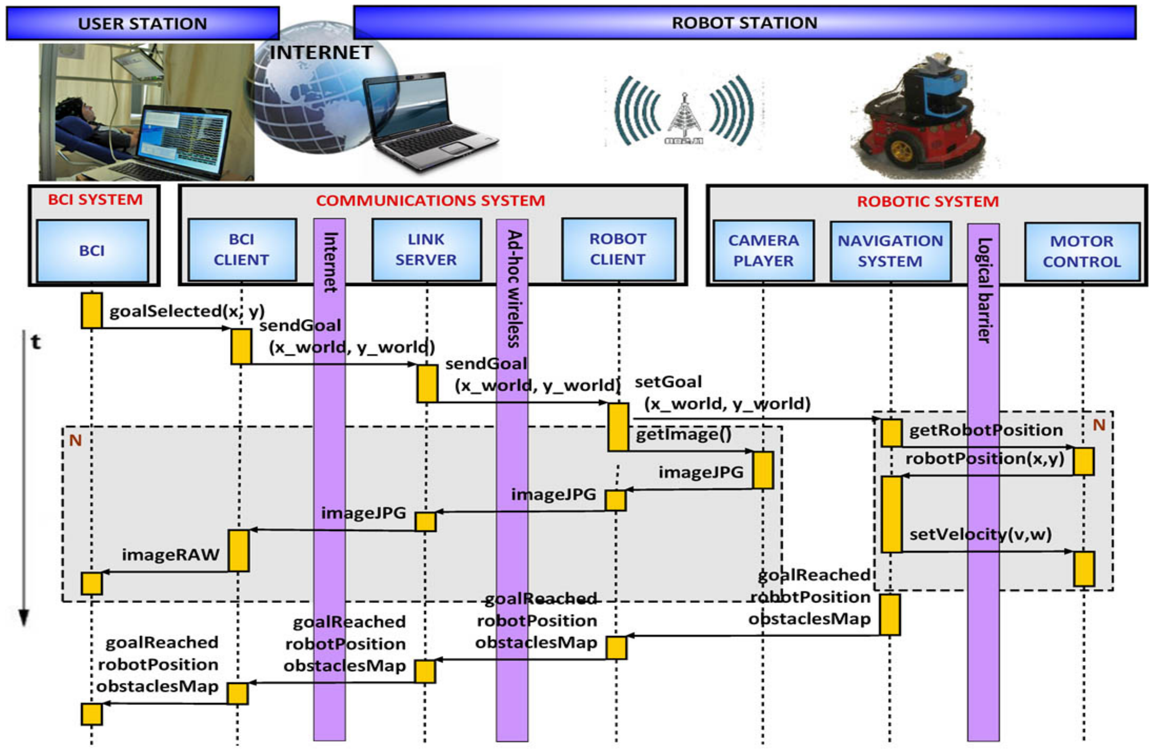


Fig. 5. The figure shows the abstraction layers: the first row represents the two stations, the second row the computer hardware and the links between them, whereas the third row represents the logical components. Below them, a typical event trace of a goal selection in the robot navigation mode is shown. The flow of information and its direction are illustrated by arrows. Vertically, time increases downward, and the vertical rectangles below boxes stand for a code execution. The dark boxes enveloping certain portions of code and information exchange represent an iterative execution task.

criteria were: (i) subjects within the age group $20 - 25$ years of age; (ii) gender (either all women or all men); (iii) laterality (either all left-handed or all right-handed); and (iv) students of the engineering school of the University of Zaragoza. The exclusion criteria were: (i) subjects with history of neurological or psychiatric disorders; (ii) subjects under any psychiatric medication; and (iii) subjects with episodes of epilepsy, dyslexia or experiencing hallucination.

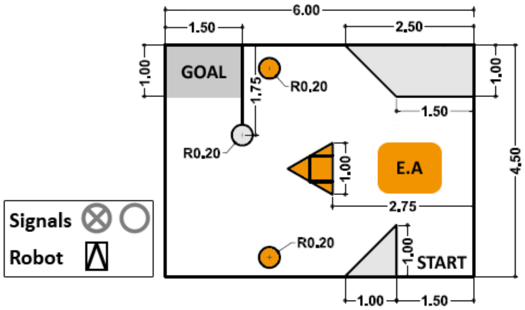
Five healthy, 22 year-old, male and right-handed students of the University participated in the experiments. None of them had utilized the teleoperation system before. The participants were duly informed about the entire protocol of the study before signing the consent forms. Permission to reproduce video recording and photographic images was duly granted by the subjects.

B. Experiment Design and Procedures

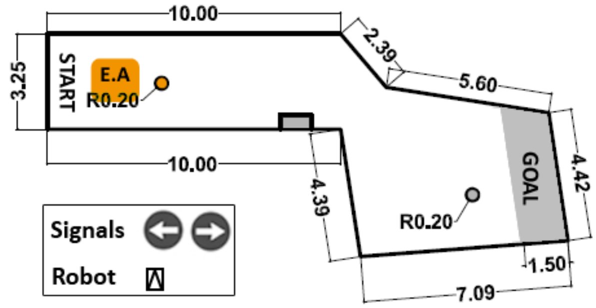
The study was accomplished in two phases: (i) screening and training evaluation, and (ii) brain-actuated teleoperation evaluation.

1) Screening and Training Evaluation: The objectives of this session were: (i) to come up with the aesthetic factors of the graphical interface that equilibrated the subject's capabilities and preferences with the performance of the system (recall that the elicitation time and the amplitude of the P300 potential are correlated with the saliency of the stimulus in terms of color, contrast, brightness, duration, etc. [10]; which affects the accuracy of pattern recognition); and (ii) to evaluate whether the subjects were ready to participate in the next phase. Regarding the first objective, the aesthetic factors of the visual display were selected based on the results of a parallel study [18], and an experimental session was designed with 8 screening trials to study whether this interface elicited the desired neurological phenomenon. Regarding the second objective, the system was trained with the previously recorded EEG and a session was designed to check whether the accuracy of the system was greater than a threshold value set to 90%, qualifying the subject for the second phase. For each subject, this session lasted 3 hours.

2) Teleoperation Evaluation: The objective of this battery of experiments was to test the brain-actuated teleoperation technology between two cities, recording data for a posterior evaluation. The experiments were accomplished the week of June 23, 2008, between the BCI laboratory at the University of Zaragoza (Spain) and the University of Vilanova i la Geltrú (Spain), separated by 260km. Two tasks were designed, which combined navigation and visual exploration in unknown scenarios and under different working conditions: the first task involved navigation in constrained spaces with an active search of two visual targets, and the second task involved navigation in open spaces with an active search of one visual target (Figure 6). Notice that the only information of the remote scenarios shown to the subjects was the plans referenced above, and that the subjects had never visited the locations. Each subject had to perform two trials per task.

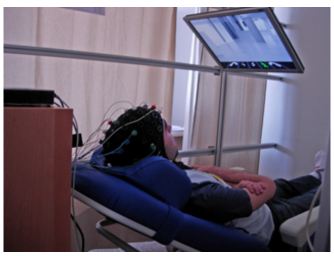


(a) Task 1

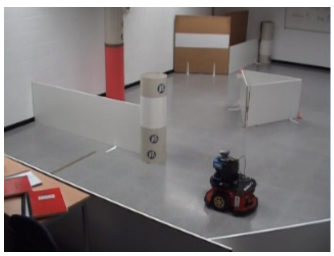


(b) Task 2

Fig. 6. (a) The objective of Task 1 was to drive the robot from the *start* location to the *goal* area. In the exploration area (E.A. in the figure), the subject had to search for two signals located in the yellow cylinders 2.5m above the floor. Then, if both signals were equal, the subject had to avoid the yellow triangle by turning to the right-hand side, or if otherwise, by turning to the left-hand side. (b) The objective of Task 2 was to drive the robot from the *start* location to the *goal* area. In the exploration area, the subject had to search for one signal located in the yellow cylinder 2.5m above the floor. The subject then had to continue navigation to the right or left direction of the two cylinders, as specified by the signal. All measures are in meters and the robot is to scale.



(a) User station



(b) Robot station

Fig. 7. (a) The user is lied down, concentrated on the options shown in the visual display and connected to the BCI system. (b) The robot is placed in a remote environment.

For each subject, this session lasted 4 hours.

VI. Results and Evaluation

This section reports the results of the experiments previously described, focusing on the evaluation of the teleoperation system.

The first phase was a screening and training session. Regarding its first objective, it was found by visual inspection of the EEG data recorded in the screening trials that the P300 potential was elicited for all subjects. Then, the pattern recognition strategy was trained and the subjects performed the online tests. All of them achieved more than 93% BCI accuracy; and thus, all of them were qualified to carry out the next phase.

The second phase consisted of the execution of the previously defined tasks, jointly combining navigation and visual exploration (Figure 7 shows the experimental settings). On the basis of these experiments a technical evaluation of the teleoperation system and its two main functionalities (the brain-computer system and the robotic system) are next described. The overall result is that all the subjects were able to successfully operate the device, reporting no failures and showing a hight robustness.

A. Overall Brain-Teleoperation System Evaluation

Following [19], [18] the subsequent metrics are proposed for the study:

- Task success.
- Number of collisions.
- Time (sec): total time taken to accomplish the task.
- Path length (m): distance traveled by the robot.
- Number of missions to complete the task[1].
- BCI accuracy: accuracy of the pattern recognition.

The results are summarized in table I.

TABLE I

Metrics to evaluate the overall system performance

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
Task success	1	1	1	0	1	1	1	0
# collisions	0	0	0	0	0	0	0	0
Time (sec)	685	1249	918	163	706	1126	910	154
Path length (m)	10.99	13.53	11.84	0.90	19.68	21.83	20.68	0.63
# missions	12	19	13.9	2.30	10	15	11.70	1.64
BCI accuracy	0.83	1.00	0.92	0.07	0.78	1.00	0.89	0.07

All subjects succeeded in solving the tasks with no collisions, which is the best indicator of the device utility. The path length and the number of missions were similar for all subjects indicating a similar performance between them. The interaction with the device was satisfactory since the lowest BCI accuracy was of 78% when the average was approximately of 90%. The variability of the total time between subjects is significant since the BCI accuracy and the number of sequences in the stimulation process changed from subjects to subjects (a higher number of sequences involves a higher BCI accuracy, but also a higher duration of the stimulation process; thus, the number of sequences was customized for each subject).

In summary, these results are very encouraging since they showed the feasibility of this technology to solve tasks (covering many of the typical real situations) in which navigation and visual exploration were needed. Recall that both tasks were designed to test the combination of both teleoperation modes under different working conditions (navigation in constrained and open spaces; and visual search of one or two targets that do not fit in the initial camera field of view).

[1]Missions are defined in subsection II-D.

B. Brain-Computer System

This evaluation was divided into two parts: an evaluation of the pattern recognition strategy and of the visual display design. Based on [20], [19], the following metrics were proposed to assess the **pattern recognition strategy**:

- Real BCI accuracy: BCI recognition rate.
- Useful BCI accuracy: ratio of good selections plus useful errors per total number of selections.
- Total BCI errors: incorrect selections.
- Useful BCI errors: incorrect selections that were reused to accomplish the task.
- Number of selections per minute.
- Usability rate: number of selections per mission.
- Number of missions per minute.
- Number of sequences in the stimulation process.
- Information transfer rate (ITR): number of bits per minute transferred from the user to the machine.

The results are summarized in the upper section of table II.

TABLE II
METRICS TO EVALUATE THE BRAIN-COMPUTER SYSTEM

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
Real BCI acc.	0.81	1.00	0.90	0.08	0.73	1.00	0.86	0.09
Useful BCI acc.	0.83	1.00	0.92	0.07	0.78	1.00	0.89	0.07
# total errors	0.00	7.00	3.50	2.88	0.00	11.00	4.9	3.7
# useful errors	0.00	2.00	0.60	0.84	0.00	5.00	1.20	1.81
# selections/min	3.39	5.49	4.41	0.72	3.40	4.77	4.16	0.46
Usability rate	2.11	3.08	2.54	0.34	2.36	3.40	2.80	0.39
# missions/min	1.17	2.27	1.77	0.39	1.00	2.02	1.53	0,33
# sequences	6	10	8	1.33	8	10	8.4	0.84
ITR (bits/min)	9.97	21.73	16.05	3.83	9.86	20.62	14.32	3.33
# misunderstandings	0	0	0	0	0	1	0.10	0.32
# far goals	0	2	1.40	0.84	2	6	4.70	1.16
# turns	2	6	3.70	1.57	0	3	0.80	1.03

According to convention [21], a person is able to use a BCI when the achieved accuracy is above 80%. In the experiments, an average BCI accuracy higher than 80% was obtained for both tasks; the real accuracies were of 90% and 86%, respectively. There is a distinction between real and useful accuracy because in some situations, although the BCI detection fails, the selections are reused to achieve the tasks. These BCI errors, referred to as useful errors, made the useful accuracy (92% and 89%) greater than the real accuracy count percentage, thus obtaining a higher accuracy. The BCI system set only two incorrect missions in all the executions, representing 0.78% of the missions (the theoretical probability of this situation is 0.3%). The stimulation process followed in this study set the number of selections per minute depending on the number of sequences (it was the only scheduling value that changed among subjects). On average, 4.41 and 4.16 selections per minute were carried out, respectively. These values establish an upper boundary for the number of missions per minute since a mission can be set with 2 selections if there are no BCI detection errors. In practice, the usability rate was slightly greater than 2 due to BCI detection errors and interface misunderstandings; thus, the number of missions per minute turned out to be lower than the middle of the average selections per minute (an average of 1.77 and 1.53, respectively).

The second part of the brain-computer system evaluation is the **visual display design**. Based on [19], [18] the following metrics were proposed:

- Number of errors caused by misunderstanding in the interface.
- Number of far goals and turns in the navigation mode.

The results are summarized in the lower section of table II.

In general, the design of the interface was acceptable since all subjects were able to solve the tasks using the functionalities provided. There was only one incorrect selection due to misunderstandings, which arose at the very end of one trial (the subject set an unreachable mission, located behind the goal wall). The frequency of usage of some commands (far goals and turns) suggests that the subjects perform the driving tasks in a different way, as reported in similar studies [19]. Regarding the BCI in general, an important aspect is the information transfer rate. A common problem of all event-related potential approaches is the low ITR values (on average the transfer rate was approximately 15 bits/min). In this system, low ITR values are not very harmful since the automation facilities provided by the robotic system (mainly the autonomous navigation system) avoids the need of a large amount of information transfers to complete difficult tasks.

In summary, these results indicate that the integrated design of the brain-computer system was suitable for controlling the brain-actuated teleoperation system.

C. Robotic System

Based on [19], a set of metrics was proposed to evaluate the **robot navigation system** of the robot: number of navigation missions, number of collisions, length traveled per mission, time per mission, mean velocity of the robot, and the minimum and mean distance to the obstacles (obstacle clearance). Moreover, the following metrics were proposed to evaluate the **camera exploration system**: number of exploration missions, and the total angle explored by the camera. All the results are summarized in table III.

TABLE III
METRICS TO EVALUATE THE ROBOTIC SYSTEM

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
# missions nav.	7	12	9.00	1.6	7	11	8.7	1.2
Length(m)/mission	1.06	1.61	1.34	0.18	1.90	2.81	2.41	0.29
Time(s)/mission	58.75	95.50	72.99	11.42	70.25	98.63	81.74	8.30
Velocity (m/sec)	0.05	0.07	0.06	0.01	0.08	0.10	0.10	0.01
Clearance min (m)	0.89	1.12	1.03	0.07	1.09	1.19	1.14	0.03
Clearance mean (m)	2.22	2.47	2.40	0.07	3.16	3.23	3.20	0.02
# missions exp.	4	7	4.9	1.2	2	5	3	1.1
Exploration (rad)	1.21	6.37	2.79	1.56	0.16	0.88	0.37	0.25

In total, the navigation system successfully carried out 177 missions without collisions, traveling a total of 325 meters with a mean velocity of $0.08\frac{m}{sec}$ (10 times less than usual human walking velocity). The average velocity and the length traveled per mission were greater in Task 2 than in Task 1, which indicates that the navigation system adapted to the different conditions of the tasks, obtaining a velocity increase in open spaces (Task 2) and a reduction when maneuverability became more important (Task 1). The mean and minimum clearances show that the robot avoided obstacles within safety margins, which is one of the typical difficulties in autonomous navigation [14].

The camera system performance was very high since all the exploration tasks were solved (all the subjects identified the correct path in the circuits). A total of 79 missions were carried out, exploring a total angular distance of 32 radians. The explored angle was greater in Task 1 than in Task 2, which also indicates that this system adapted to the conditions of the tasks.

In general, the performance of the navigation and exploration systems was remarkable since all tasks were successfully solved by the combination of both systems, reporting no failures.

VII. Conclusions

This paper describes an EEG-based human brain-actuated robotic system to carry out teleoperation tasks between remote places via internet. In operation the user can combine two teleoperation modes: robot navigation and camera control. Both modes turn to be crucial to solve visual exploration tasks where the robot must also navigate in the environment. This brain-actuated robot teleoperation has been validated with five healthy subjects, which performed pre-established navigation and visual exploration tasks for one week between two cities 260km far away. The overall result is that all the subjects were able to successfully solve all the tasks reporting no failures, showing a high robustness of the system. This study shows for the first time the feasibility of this technology in humans and using non invasive techniques.

In near future, the researchers are working on the improvement of the system to address the common problem of all event-related potential approaches: the low information transfer rate. In this direction, a P300 continuous control of the system is being developed, in an attempt to reduce the total time to solve the tasks. Another shortcoming of these systems is that with the synchronous operation, the user has to be continuously concentrated in the task. An interesting improvement the researchers would like to work is the adoption of asynchronous P300 control to support an idle state, as in [22]. Although the BCI accuracy was high, the integration of BCI-based online error detection system is being worked on also. Furthermore, the researchers are working on the incorporation of high level tasks in teleoperation to improve navigation (e.g., with tasks such as people-tracking and following), camera control (e.g., tracking and aligning the camera with the location of specific sounds or voices); and the integration of this system in small, low-cost robots.

VIII. Acknowledgements

The authors would like to thank the *4@all laboratory of Vilanova i Geltrú (Barcelona, Spain)* for the support during the experimentation sessions. Thanks are extended to Iñaki Iturrate, María López, Belén Masiá, Luis Riazuelo and to all the participants for their support in the development of the project. This work was partly supported by the Spanish project DPI2006-15630-C02-02.

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