A Noninvasive Brain-Actuated Wheelchair Based on a P300 Neurophysiological Protocol and Automated Navigation

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***Abstract*—This paper describes a new noninvasive brain-actuated wheelchair that relies on a P300 neurophysiological protocol and automated navigation. When in operation, the user faces a screen displaying a real-time virtual reconstruction of the scenario and concentrates on the location of the space to reach. A visual stimulation process elicits the neurological phenomenon, and the electroencephalogram (EEG) signal processing detects the target location. This location is transferred to the autonomous navigation system that drives the wheelchair to the desired location while avoiding collisions with obstacles in the environment detected by the laser scanner. This concept gives the user the flexibility to use the device in unknown and evolving scenarios. The prototype was validated with five healthy participants in three consecutive steps: screening (an analysis of three different groups of visual interface designs), virtual-environment driving, and driving sessions with the wheelchair. On the basis of the results, this paper reports the following evaluation studies: 1) a technical evaluation of the device and all functionalities; 2) a users' behavior study; and 3) a variability study. The overall result was that all the participants were able to successfully operate the device with relative ease, thus showing a great adaptation as well as a high robustness and low variability of the system.**

***Index Terms*—Neurorobotics, rehabilitation robotics.**

I. Introduction

BRAIN–COMPUTER interfaces (BCIs) are systems that allow to translate in real time the electrical activity of the brain in commands to control devices. They do not rely on muscular activity and can, therefore, provide communication and control for people with devastating neuromuscular disorders, such as the amyotrophic lateral sclerosis (ALS), brainstem stroke, cerebral palsy, and spinal cord injury. It has been shown that these patients are able to achieve electroencephalogram (EEG)-controlled cursor, limb movement, and a prosthesis control and even have successfully communicated by means of a BCI (see [1]–[3] among others).

Recently, there has been a great surge in research and development of brain-controlled devices for rehabilitation. Although in animals this research has been focused on invasive methods (intracraneal), the most popular recording method for humans has been the EEG. So far, systems based on human EEG have been used to control a mouse on the screen [4], for communication like a speller [1], [5], an Internet browser [6], [7], etc. Furthermore, the research on brain–machine interfaces applied to human control of physical devices has been broadly focused mainly in two directions: neuroprosthetics and brain-actuated wheelchairs. Neuroprosthetics focuses on the motion control or hand orthosis, which usually improves the upper body possibilities of users with mobility impairments, such as reachability and grasping [8]–[10]. Wheelchairs focus on the facilitation of assistance in mobility to accomplish complex navigational tasks to improve quality of life and self-independence of users.

Following the noninvasive brain-actuated robot control demonstrated in 2004 [11], there have been some attempts to develop a brain-actuated wheelchair. Some devices follow the clinical protocol where the EEG signals are synchronized with visual, auditory, or tactile events or stimuli, using one of the common event-related potentials (evoked potentials in the human brain associated with external stimuli; see [12] for review). One example is the wheelchair developed by Gräser *et al.* [13], which uses steady-state potentials [14]. These potentials are visually elicited by a stimulus modulated at a fixed frequency and appear as an increase in EEG activity at the stimulus frequency. Another example is the Rebsamen *et al.* wheelchair [15],which uses P300 potentials [16]. These potentials manifest themselves as a positive deflection in the EEG at a latency of approximately 300 ms, after the desired target stimulus (visual, auditory, or tactile) is presented within a random sequence of nontarget stimuli. Both devices use high-level motion primitives (e.g., go to the kitchen) in a menu-based system. Another synchronous device is the Ferreira *et al.* wheelchair,which uses the desynchronization of alpha rhythms in the visual cortex that occur when the eyes are open or closed [17].[1] This desynchronization is used as a binary input to select low-level motion primitives (e.g., front, back, left, and right) in a sweeping menu-based system. From an interactional point of view, the advantage of these synchronous prototypes is the high accuracy in the thought-recognition

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[1]Note that this is a neurological phenomenon that requires the control of the blinking muscular process.

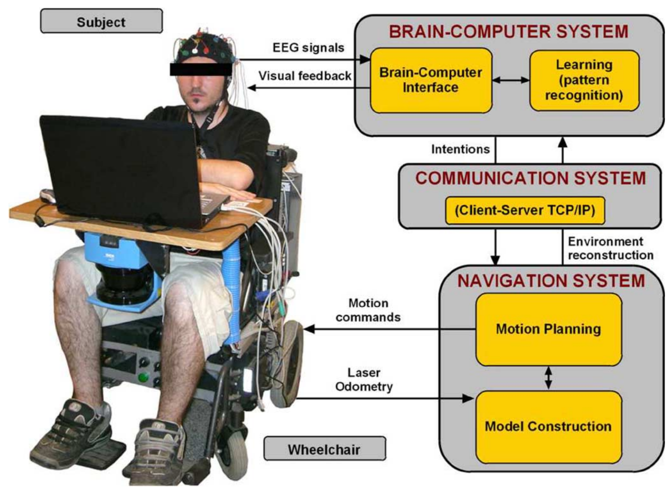


Fig. 1. Mechatronic design of the brain-actuated wheelchair, the main modules, and information flow.

process (above 94%). However, these protocols have low information transfer rates (approximately 4–15 b/min, i.e., one selection each 4–15 s) since they repeat the external cue dozens of times to improve the signal-to-noise ratio. From a navigational point of view, the advantage is that the user does not need to concentrate while the robot executes navigation. However, systems based on high-level navigation limit the wheelchair to move in preprogrammed and static scenarios. On the other hand, systems based on low-level navigation (e.g., front, back, left, and right) rely on very slow motions (accommodating to the information transfer rate), even in simplistic scenarios.

Another wheelchair concept was jointly developed by Vanacker *et al.* [18]. This device is based on an asynchronous protocol that analyzed the ongoing EEG activity to determine the user's mental state, which can change at any time. The system deciphers the user's steering directions (forward, right, and left) and uses an obstacle avoidance system that executes navigation. From an interactional point of view, the great advantage is that brain control is spontaneous (not attached to external cues, adding a new degree of freedom for the user) and doubles the usual bit rates of the synchronous' approaches, with a precision of approximately 65%. However, the mental process requires constant mental effort for the user. From a navigational point of view, the safety of the system was improved with the inclusion of an obstacle avoidance system, which filters commands (possibly erroneous) that could lead to collisions.

A. Overview and Contributions

This paper describes a new brain-actuated wheelchair concept that relies on a synchronous P300 neurophysiological protocol integrated in a real-time graphical scenario builder, which incorporates advanced autonomous navigation capabilities (see Fig. 1). When in operation, the user faces a screen displaying a real-time virtual reconstruction of the scenario, which is constructed by a laser scanner. On the basis of this representation, the user concentrates on the location of the space to reach. A visual stimulation process elicits the neurological phenomenon, and the signal processing detects the target area. This location is then given to the autonomous navigation system that drives the wheelchair to the desired location while avoiding collisions with the obstacles detected by the laser scanner. From an interactional point of view, this system has similar properties to those of the P300-based synchronous BCIs (high accuracy but low transfer rates). This is because accuracy was considered important in the selection process (above 94%), given the critical safety nature of the device [19]. Despite the low information transfer rate (two orders per minute), once the order is given, the user can relax, since the navigation is automated, thus avoiding the exhausting mental processes of other devices. From a navigational point of view, the great advantage is that the user selects destinations from a set of generated points in the environment (medium-level commands) that are safely and autonomously reached by the navigation system. This is because the system incorporates real-time adaptive motion planning and modeling construction of the scenario, and thus, it is able to deal with nonprepared and populated scenarios. Furthermore, the automation in the navigation process allows the maneuverability in complex scenarios using the state-of-the-art technology in robotics. This human–robot interaction framework improves the information flow between the user and the robot since it involves medium-level task-relevant interaction (selection of points of the space to reach), which is more efficient than lower level schemas (selection of direction of motion), and due to a navigation technology that expands these task-relevant commands into a complex motion activity in the real world [20].

This paper has paid due attention to the methodology and experimental validation of the device. In this direction, the prototype was validated with five healthy participants in three consecutive steps: screening, virtual-environment driving (training and instruction of participants), and driving sessions with the wheelchair (driving tests along established circuits). On the basis of the results, this paper reports the following evaluation studies: 1) a technical evaluation of the device and all functionalities (i.e., the BCI, graphical interface, and navigation technology); 2) a users' behavior study based on an execution analysis, an activity analysis, and a psychological analysis; and 3) a variability study among trials and participants. The overall result is that all the participants were able to successfully use the device with relative ease, thus showing a great adaptation as well as a high robustness and low variability of the system.

II. Brain–Computer System

A. Neurophysiological Protocol and Instrumentation

There are two broad categorizations of EEG-based BCI systems: those that are controlled by the voluntary modulation of the brain activity [21], [22] and those based on an event-related response to an external stimulus [23], [24]. In the latter category, the user focuses attention on one of the possible visual, auditory, or tactile stimulus, and the BCI uses the EEG to infer the stimulus to which the user is attending. The neurophysiological protocol followed in this study was based on the P300 visually evoked potential [16]. This potential manifests itself as a positive deflection in the EEG at a latency of approximately

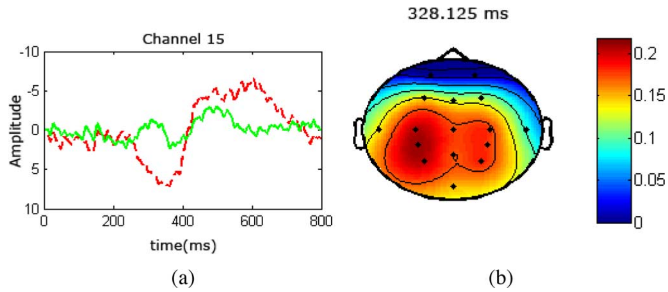


Fig. 2. (a) Typical P300 response. The dashed line shows the EEG activity on one channel (elicited by the target stimulus), and the solid line corresponds to the non-target stimuli. (b) Topographical plot of the distribution of r^2 values (which indicates the proportion of single-trial signal variance that is due to desired target [25]) on the scalp at 300 ms. The parietal and occipital lobes (mid-low part of the scalp) are the areas with highest r^2.

300 ms, after the desired target stimulus is presented within a random sequence of nontarget stimuli. Roughly, it is elicited in the electrodes covering the parietal lobe (see Fig. 2). A characteristic of this potential, relevant to this BCI system, is that neurophysiological studies [16] revealed that the elicitation time and the amplitude of the potential were correlated to the fatigue of the user and the saliency of stimulus (in terms of color, contrast, brightness, duration, etc). The generalinstrumentation of the BCI was a commercial gTec EEG system (an EEG cap, 16 electrodes, and a gUSBamp amplifier) connected via Universal Serial Bus (USB) to the onboard computer. The location of the electrodes was selected according to previous P300 studies [26], at FP1, FP2, F3, F4, C3, C4, P3, P4, T7, T8, CP3, CP4, Fz, Pz, Cz, and Oz, according to the international 10/20 system. The ground electrode was positioned on the forehead (position FPz) and the reference electrode was placed on the left earlobe. The EEG was amplified, digitalized with a sampling frequency of 256 Hz, and power-line notch-filtered and bandpass-filtered between 0.5 and 30 Hz. The signal recording and processing, as well as the visual application, were developed under BCI2000 platform [25] and placed on an Intel Core2 Duo at the rate of 2.10 GHz running Windows XP OS. From now on, this computer will be referred to as the high-level computer.

B. Graphical Interface

In order to command the wheelchair, the user must select destinations or motion primitives by concentrating on the possibilities displayed on the computer screen [see Fig. 3(a)]. The graphical interface 1) displayed information of the real-time reconstruction of the environment and additional information for the order selection and 2) developed the stimulation process to elicit the P300 visual evoked potential.

1) Visual Display: The graphical aspects of this module were based on a previous study involving a robotic wheelchair with a tactile screen, adapted for cerebral palsy users [27]. The information displayed on the screen was a reconstruction of the real scenario for the user's command selection [see Fig. 3(b)]. The environmental 3-D visualization was built from a 2-D map constructed in real time by the autonomous navigation technology. The use of a sensor-based online map instead of an *a priori* map endowed the system with the necessary flexibility to work in unknown and evolving scenarios (sensor-based maps rapidly reflect changes in the environment, such as moving people or unpredictable obstacles like tables or chairs). To facilitate the user's awareness of the situation, the map was displayed on the screen, originating from a virtual camera located at the operator's eye level. In other words, the visual information on the screen was a simplified reconstruction of the user's perception.

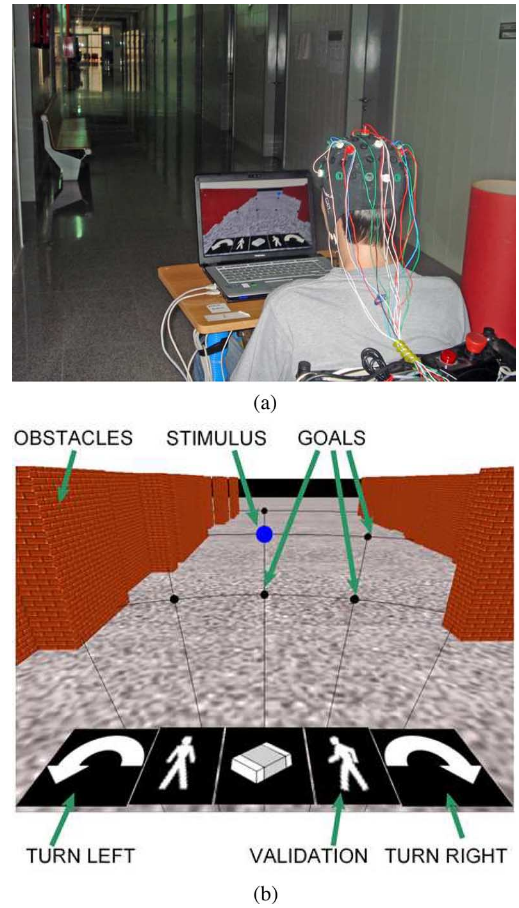


Fig. 3. (a) Snapshot of a participant navigating along a corridor. (b) Information represented in the visual display, which is an environment abstraction displayed from the user's point of view.

The rest of the displayed information was used for command selection [see Fig. 3(b)]. First, there was a predefined set of destinations relative to the wheelchair's location within the map, which corresponded to locations in the environment that the participants might select to reach. These locations were represented in the display by an $N \times M$ polar grid referenced to the wheelchair. The grid intersections represented real locations in the scenario, and its dimension was customizable. In this case, a grid was used to represent locations at $(2\text{ m}, 4\text{ m}, 8\text{ m}) \times (-60^\circ, -30^\circ, 0^\circ, 30^\circ, 60^\circ)$ from the current wheelchair location, where the first grid row was the one with farthest destinations. The obstacles were depicted by walls, which hid the unreachable destinations of the grid. In addition to this, there were also specific actions available, represented by icons at the lower section of the visual display. The first set of actions turned the vehicle $\pm 90^\circ$ in reference to its current position. The icons were located on the right- and left-hand sides of the lower part of the screen, and were represented by a turning arrow in the respective directions; the traffic light buttons validated the user's commands or stopped the vehicle, and the eraser represented the "remove selection" option. In the current version of the interface, the "stop" and "remove selection" options were not used, but they have been taken into account for the next interface prototype.

All elements shown on the display could be customized in terms of color, texture, shape, size, and location. This was important in the screening sessions to equilibrate the user's capabilities and preferences with the performance of the system (recall that the shape and the latency of the P300 potential were correlated to these visual aspects).

2) Stimulation Process: The other aspect of the graphical interface was the stimulation process to elicit the P300 visual evoked potential when the user was concentrating attention on a given option. An option was "stimulated" by displaying a circle on the selection [see Fig. 3(b)]. One sequence of the stimulation process was a stimulation of all options in a random order as required by the P300 oddball paradigm. Note that this process required 20 stimulations (number of options in this display) and imposed a subsequent 20-class classification problem for the pattern recognition strategy. In order to reduce the duration of a sequence and the dimension of the pattern-recognition problem, the Farwell and Donchin [23] stimulation paradigm was followed. In this paradigm, the flashing of the stimuli was carried out by means of rows and columns instead of flashing each option individually. Thus, in this interface, there were nine stimulations (number of rows plus number of columns) and two classification problems of five and four classes (the target option is the intersection of the target row and target column). The number of sequences and all scheduling of the stimulation process (exposition time of each stimulus, interstimulus duration, and intersequence duration) could 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 that is trained to recognize the P300 evoked potential and, thus, to infer the stimulus that the user is attending to. The first step was to train the system via offline experiments, where the user faced the graphical interface with the stimuli described before. In this process, the user concentrated on a previously predefined sequence of selections that covered all classes. The data were recorded and used to train the classification algorithm using a supervised learning technique consisting of two steps: feature extraction and classification algorithm.

In order to extract the features, Krusienski *et al.*'s study [26] was followed as the feature extraction technique. The P300 signals were characterized in the time domain; therefore, the information was in its waveform and latency times. In this study, for each EEG channel, 1-s sample recordings were extracted after each stimulus onset. These segments of data were then filtered using the moving average technique and decimated by a factor of 16. The resulting signals were plotted and the channels with the best P300 response were selected by visual inspection (the selected number of channels varied between six and ten, depending on the participant). The resulting data segments for each channel selected were concatenated, creating a single-feature vector for the next stage (i.e., if ten channels were selected, the length of feature vector was 256/16 samples $\times$ 10 channels $=$ 160).

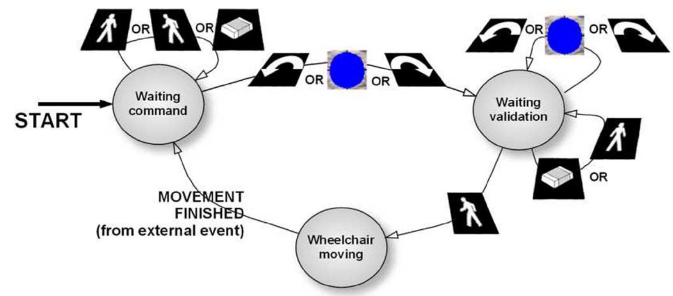


Fig. 4. Finite-state machine that models the execution protocol of the options displayed on the screen to command the wheelchair.

The next step was the classification algorithm. In this system, the P300 signal was elicited for one of the four rows or five columns during the sequence of stimulation. Thus, there were two classification problems of four and five classes. For each of these subproblems, the stepwise linear discriminant analysis (SWLDA) was used, extensively studied for P300 classification problems [23], and used with very good results in online communication using visual stimulation [28] and auditory stimulation [29]. Briefly, SWLDA is an extension of the fisher linear discriminant analysis (FLDA), which performs a reduction in the feature space by selecting the most suitable features to be included in a discriminant function (FLDA looks for a separating hyperplane subdividing the feature space into two classes by maximizing the distance between the averages of the two classes, as well as and also minimizing the variances of the data features inside each class). In this system, SWLDA was used for the P300 classification, obtaining a performance higher than 90% in less than an hour of training for every participant that performed the experiments.

D. Execution Protocol

The execution protocol was the way the participant utilized the possibilities of the visual display described in Section II-B (communication protocol between the user and the wheelchair). This protocol was modeled by a finite-state machine (see Fig. 4). Initially, the state is *waiting command*. In this state, the wheelchair is stopped (i.e., not performing any action). When the user concentrated on one of the options, the BCI developed the stimulation process and, if the pattern recognition did not make an error, the desired option was selected. When the option was a command (either a destination or a turn), the state changed to *waiting validation*. In this state, the BCI developed the stimulation process, and a new option was selected. If the option was the validation, the relevant action was transferred to the autonomous system of the wheelchair (command plus validation is referred to as a *mission*), and the state changed to *wheelchair moving*; otherwise, the stimulation process restarted until a command was selected and later validated. Moreover, "stop" and "remove selection" options did not change the state or the previous selection, which would remain selected. While the state was *wheelchair moving*, the stimulation process was blocked (i.e., there was no stimulation), and the system waited for an external flag from the autonomous navigation system, thus informing that the command was executed. Once the flag was received, the state changed to *waiting command*.

III. Robotic Wheelchair

This section describes the robotic wheelchair. First, the mechatronic design of the device is described, including the computers and the sensors, and then the autonomous navigation system that performs the model building and local planning is also described.

A. Mechatronic Design

The robotic wheelchair was constructed based on a commercial electric wheelchair that complied with the basic user mobility and ergonomic requirements (see Fig. 1). Two Intel Pentium III 800 MHz computers were installed onboard. The first computer performed the low-level control (real-time operative system, VxWorks) controlling the rear wheels that work in a differential-drive mode. The second computer was used for medium-level control, performing the navigation computations and managing the communications between the wheelchair and the BCI system. Both computers were connected via RS-232 and Ethernet. The main sensor was a SICK planar laser placed at the frontal part of the vehicle, operating at a frequency of 5 Hz, with a 180° field of vision and a 0.5° resolution (361 points).This sensor provided information about the obstacles in front of the vehicle. The wheelchair was also equipped with wheel encoders to measure the odometry (position and orientation). In the experiments, the maximum translational and rotational velocities were set to $v_{\max} = 0.3$ m/s and $w_{\max} = 0.7$ rad/s, respectively, based on experience with participants using the wheelchair [27].

B. Autonomous Navigation System

The task of the autonomous navigation system was to drive the vehicle to a given destination while also avoiding obstacles (both static and dynamic) detected by the laser sensor. The goal location was provided by the user by means of a BCI (see the previous section). As mentioned in Section I, this medium-term navigation implemented with online modeling and planning capabilities allowed the system to provide mobility skills, even in situations where the user was moving in an unknown environment (which prevented predefined strategies) or where the environment varied with time (e.g., moving people or changes in the location of furniture). In order to implement such a complex navigation system, it was necessary to combine several functionalities [30] integrated on two modules: the model builder and the local planner.

The model builder integrated the sensor measurements to construct a local model of the environment and track the vehicle location. A binary occupancy grid map was chosen to model the static obstacles as well as the free space, and a set of extended Kalman filters was chosen to track the moving objects around the robot. A specific technique [31] was used to correct the robot's position, update the map, and detect and track the moving objects around the robot. The static map traveled centered on the robot. This map had a limited but sufficient size to present the required information to the user (as described in the previous section) and to compute the path in order to reach the selected goal.

The local planner computed the local motion based on the hybrid combination of tactical planning and reactive collision avoidance. An efficient dynamic navigation function (D*Lite planner [32]) 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 was computed using the nearness diagram (ND) technique [33], which uses a "divide and conquer" strategy, based on situations and actions to simplify the collision avoidance problem. This technique has the distinct advantage that it is able to deal with complex navigational tasks, such as maneuvering in the environment within constrained spaces (e.g., passage through a narrow doorway). In order to facilitate comfortable and safe operation during navigation, shape, kinematics, and dynamic constraints of the vehicle were incorporated [30].

IV. Communication System and Integration

The communication system performs the integration between the brain–computer system (see Section II) and the robotic system (see Section III), which operated as the link between them, managing all the tasks related with the synchronization and information flow (see Fig. 1).

The system was based on a Transmission Control Protocol (TCP)/IP connection between the high-level computer (that ran the BCI) and the medium-level computer of the wheelchair (that ran the navigation system) (see Fig. 5). The software architecture was composed of a server and two clients, integrated within the previous systems: 1) The BCI client was multiplexed in time with the BCI system with a period of 30 ms; 2) the wheelchair client encapsulated the navigation system as a thread; and 3) a link server located between the clients concentrated the information flow and made the system scalable for further additions. The communication between the medium-level computer and the low-level computer (wheel control) of the wheelchair was also TCP/IP based. In this case, the client was integrated within the navigation system, and the server was integrated within the low-level motion controller.

The temporal information flow and synchronization of the modules are displayed in Fig. 5. A typical execution was: first, the BCI computed a goal location (8 B of information), which was transferred to the link server via the BCI client. The

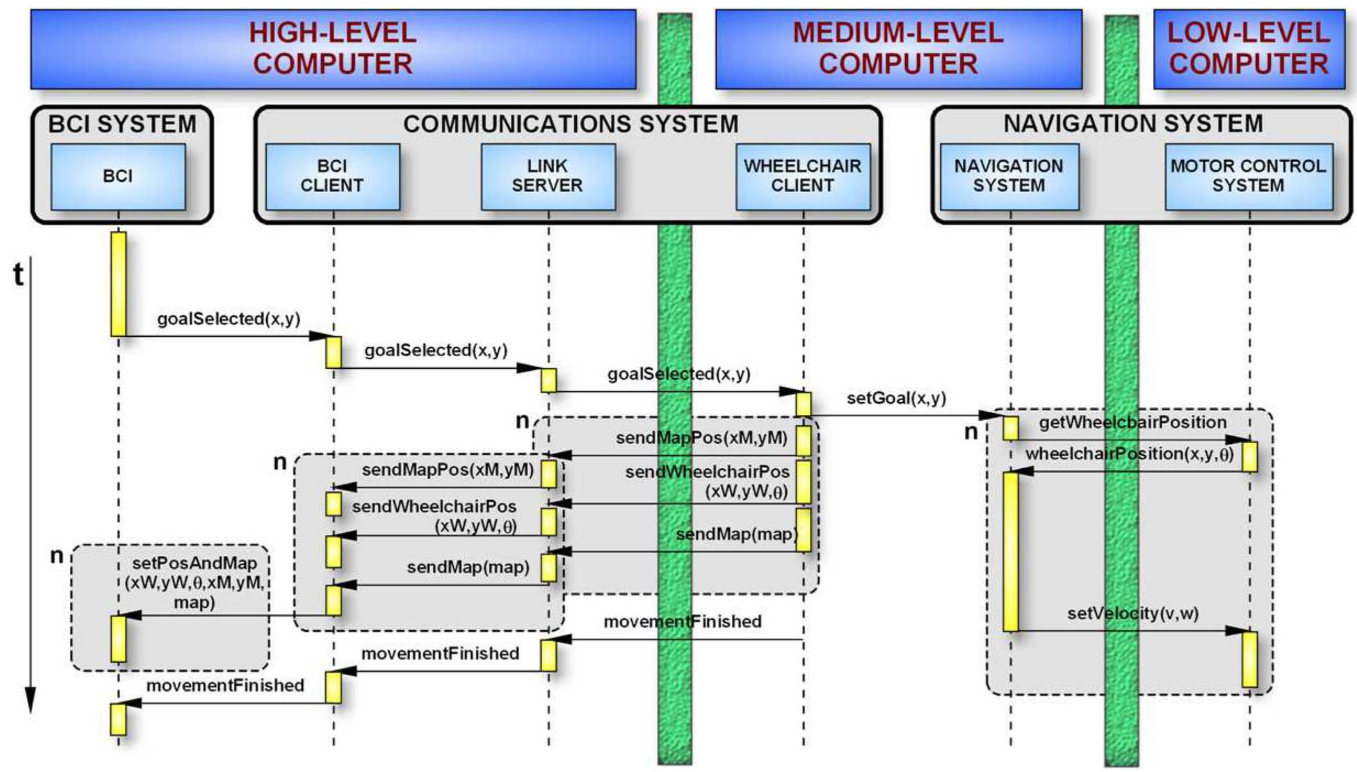


Fig. 5. First row represents the computer hardware, whereas the second row represents the logical components. An event trace of the three integrated and running computers is shown below, which illustrates a typical flow of information, starting when the user selected a destination. The flow of information and its direction are illustrated by arrows. Vertically, time increases downwards, and the vertical rectangles below the boxes represent a code execution. The dark boxes enveloping certain portions of code represent an iterative execution task.

navigation system client received this information from the server and made it available for the navigation system. Within a synchronous periodical task of 0.2 s, the navigation system read the location of the wheelchair from the motor control system and the laser sensor, requested the robot odometry from the low-level computer, executed the mapping and planning module, and sent the computed translational and rotational velocities to the low-level computer. There were three variables computed by the navigation system that needed to be transferred to the BCI: the map model (400 B), the model location (12 B), and the wheelchair location within the map (12 B). These variables, which are located in the navigation thread, were accessible by mutual exclusion by its client, which sent them to the link server that transferred them to the BCI client. When the wheelchair reached the final location, the navigation system triggered and sent a flag to stop this information transfer process. The BCI then restarted the stimulation process to obtain a new goal location.

The maximum bandwidth between the high-level computer and the medium-level computer of the wheelchair was 2 kB/s (when the navigation system was moving the wheelchair). The bandwidth of the communication between the computers of the wheelchair was 0.1 kB/s. Neither information transfer rates overcame the 100 Mb/s bandwidth of the internal network and, therefore, did not impose a significant computation time for the clients and servers.

There were two time-critical tasks in this integration: the low-level motion controller and the autonomous navigation system. The first task was encapsulated in a dedicated computer (low-level computer of the wheelchair) with a real-time operative system. The autonomous navigation system was integrated in another dedicated computer (medium-level computer) and integrated within a thread-based system with time-outs to preserve the computation cycle (0.2 s). For more information on the implementation of these tasks, see [30].

V. Validation

The objective of this study was to assess the performance and adaptability of the brain-controlled mobility device (wheelchair) driven by able-bodied users in real settings. In the following sections, the recruitment of participants is discussed, followed by a detailed account on 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. After being informed about the content and aims of the study, all participants signed informed consent.

A set of inclusion and exclusion criteria was applied for the recruitment of users in order to obtain the conclusions for the study over a homogeneous population. The inclusion criteria were 1) users within the age group 20–25 years; 2) gender (either all women or all men); 3) laterality (either all left handed or all right handed); and 4) students of the engineering school in the University of Zaragoza. The exclusion criteria were 1) users with history of neurological or psychiatric disorders; 2) users under any psychiatric medication; and 3) users with episodes of epilepsy, dyslexia, or experiencing hallucinations. In addition to these criteria, the study was constrained by ergonomic conditions so as to suit the users to the wheelchair size and design: 1) user weight of 60 ± 20 kg; 2) height of 1.70 ± 0.20 m; and 3) lean or thin bodily constitution.

Five healthy, 22-year-old male and right-handed students of the university participated in the experiments. None of them had ever utilized an electric wheelchair before. The participants were duly informed about the whole protocol of the study before they signed the consent forms. Permission to reproduce video recording and photographic images was duly granted from the participants.

B. Experiment Design and Procedures

The study was accomplished in three phases in the BCI Laboratory of the University of Zaragoza. The first phase involved a screening session and one experiment designed to select the visual aspects (colors, textures, etc.) of the graphical interface. The second phase consisted of driving training and a test on a wheelchair simulator—which emulated the underlying mechanisms of the user interface and wheelchair navigation—to train and evaluate whether the participant was ready to use the wheelchair. The last phase consisted of real-time navigation in the wheelchair along established circuits to evaluate the rehabilitation device. Each phase lasted one week. The design and procedures of the three phases as well as the ethical concerns of the study are described next.

1) Screening and Analysis of Visual Aspects of the Interface: The objective of this session was to screen the participants for the next stage and design the aesthetic factors (the color, contrast, and brightness of the stimulus and background as well as floor and wall textures) of the interface explained in Section II-B in order to equilibrate the user's capabilities and preferences with the performance of the system[2] (recall that the shape and time of the P300 potential are correlated to these visual aspects [16], which affected the performance of the pattern recognition system). An experiment was performed with three predefined groups of factors in order to limit the complexity of the experiment, which were tested as follows. One experimental test consisted of the repetition, for each group of factors, of the typical P300 screening (the participant concentrated his attention on a predefined sequence of targets of the visual display while the EEG was recorded). After each trial, the participants were asked to fill in neuropsychological and cognitive assessment forms and their level of preference for each variation of the graphical interface. This process was repeated three times, always maintaining the same order of the groups of factors. For each participant, this session lasted 3–4 h.

2) Driving Training and Wheelchair-Simulator Test: The second phase consisted of driving training and a wheelchair-simulator test to familiarize the participants with the device and evaluate whether the participant was ready to participate in the final experimentation session using the wheelchair.

This phase was accomplished in two steps. In the first step, each participant completed three experiments of P300 screening with the graphical interface to gather EEG data and train the classifier. Next, the participants performed an online accuracy test to qualify for the next phase. In the second phase, the instructor explained how to interact with the user interface so that the participants became familiar with the working protocol and its relation to the navigation task. The participants then participated in a driving test that consisted of a navigation trial with the wheelchair simulator along a virtual circuit (common for all participants). The duration of the participant's individual training varied from 45 to 60 min, depending on the participant, whereas the duration of the virtual circuit experiment lasted from 50 to 60 min. The participants that completed the virtual circuit qualified for the real wheelchair navigation.

3) Experimentation With the Brain-Actuated Wheelchair: The objective of this battery of experiments was to create the basis for a technical and users' behavior evaluation of the brain-actuated wheelchair: to explore the navigation capabilities of the system and assess the performance of the participants and their ability to accomplish complex maneuverability tasks, avoid obstacles, and navigate in open spaces in real settings.

Two circuits were designed for the participants to solve by autonomously navigating with the wheelchair (see Fig. 6). The first circuit was designed to accomplish complex maneuverability tasks and avoidance of obstacles in constrained spaces. The second circuit involved navigation in open spaces. Each participant performed two trials of the first task (named "S" circuit) and, then, two trials of the second task (named "corridor" circuit). After each trial, the participants were asked to fill in neuropsychological and cognitive assessment forms and express their feelings about the wheelchair during navigation. For each participant, this session lasted 4 h.

4) Ethical Concerns of the Study: Due heed was paid to the significance of ethical aspects in the context of the qualitative nature of this research. To comply with ethical issues, responsibility, reflection, and transparency were maintained during the conduct of the entire protocol, such as the selection of participants for the investigation, research queries, and study design. A short briefing on the research procedure was given to introduce the participants to research process, and then, participants signed informed consent. Furthermore, a research supervision was maintained during the entire study. The participants were encouraged to express themselves and were allowed to discontinue participation at any time during the experiment. The researchers gave support as facilitators during the different sessions of the study and continuously observed the participants' cognitive and emotional states (e.g., attention, frustration, or fatigue).

VI. Results and Analysis

This section reports the results of the experiments previously described. The experimental methodology had two preparatory phases before the evaluation phase of the rehabilitation device. The main results of these preparatory phases are briefly outlined (see [34] for more details).

[2]Note that different participants could have different factors, depending on the results.

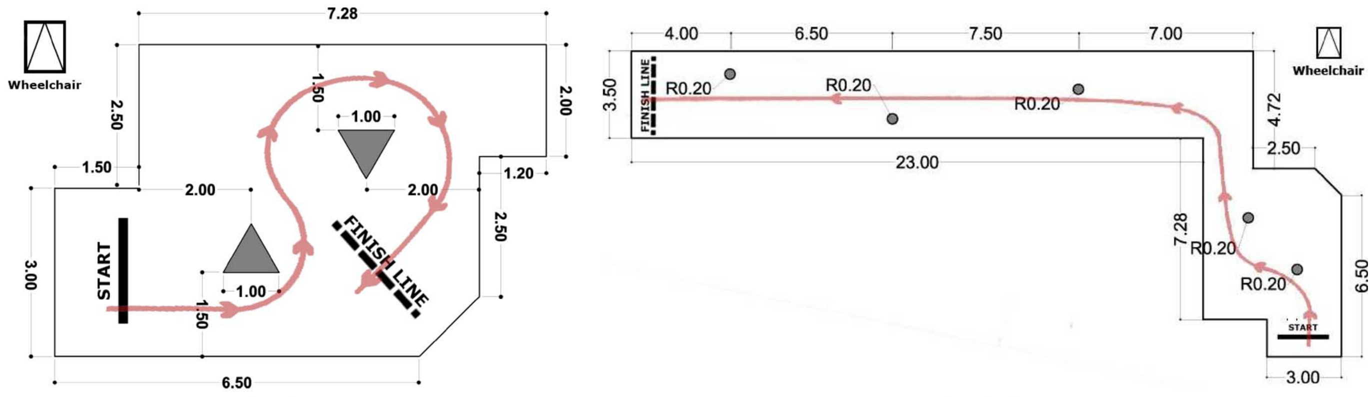


Fig. 6. Objective of task 1 was to leave the start area and to reach the finish line by passing the first triangle on the left-hand side, passing between the two triangles, and passing the last triangle on the right-hand side. The objective of task 2 was to simply reach the finish line. An example of a possible path is marked. All measures are in meters and the wheelchair is to scale. The shaded objects represent static obstacles.

The first experimentation phase was a screening session with three different graphical interfaces. To perform the analysis, two technical metrics were established and were related to 1) the quality of the signals and 2) the performance of the classifier, as well as four neuropsychological and cognitive assessment metrics: workload, user learnability, confidence, and preference. In general, the results showed that the group of aesthetic factors displayed in Fig. 3 showed the best compromise. Thus, it was decided to use this group of factors for all participants.

The second phase consisted of a driving training and a brain-actuated wheelchair-simulator test. The analysis was performed using as technical metrics the path length, time, number of missions, number of collisions, command usage frequency, and whether they completed the virtual circuit or not. All the participants completed the circuit, and they showed a high understanding of the interface and navigation performance, and thus, all qualified.

The last phase consisted of real-time navigation with the wheelchair along established circuits. On the basis of these experiments, this section describes an evaluation of the rehabilitation device. Three different but complementary points of view are focused on a performance study of the intelligent wheelchair, a users' behavior study, and a variability study among trials and participants. The overall result of the experiments was that all the participants were able to carry out the navigation tasks along the established circuits with relative ease (see Fig. 7).

A. Intelligent Wheelchair Performance Evaluation

This section describes a general evaluation of the brain-actuated wheelchair and a particular evaluation of its two main systems: the brain–computer system and the navigation technology.

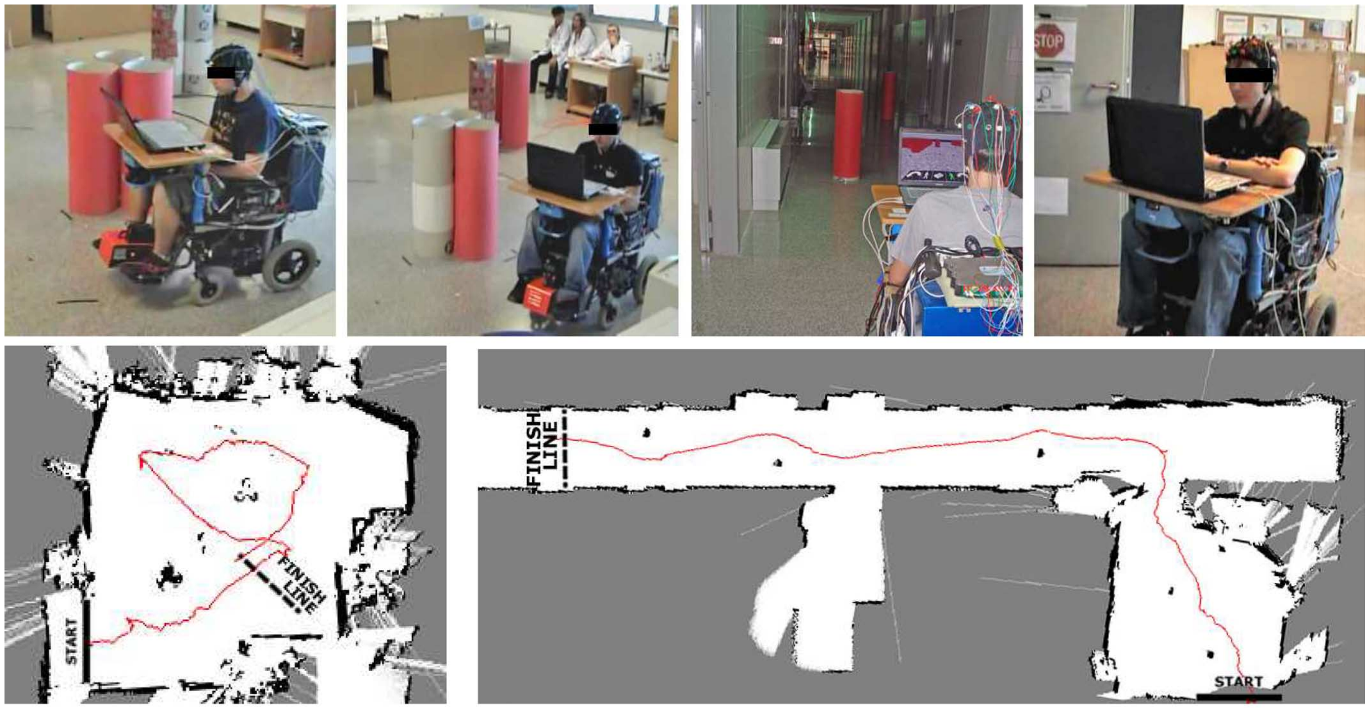
1) Overall Performance: The metrics proposed in [27] were followed to evaluate the performance of autonomous wheelchairs.

1) *Task success:* degree of accomplishment of the navigation task;
2) *Path length:* distance in meters traveled to accomplish the task;
3) *Time:* time taken in seconds to accomplish the task;
4) *Path length optimality ratio:* ratio of the path length to the optimal path (the optimal path was approximated by visual inspection as 12 m for task 1 and 32 m for task 2);
5) *Time optimality ratio:* ratio of the time taken to the optimal time (the optimal time was approximated assuming an average velocity of 0.15 m/s, resulting in 80 s for task 1 and 227 s for task 2);
6) *Collisions:* number of collisions;
7) *BCI accuracy:* accuracy of the pattern-recognition strategy.

The results are summarized in Table I. All the participants succeeded to autonomously navigate along the two circuits, which was the best indicator of the device utility. The path length and time taken were very similar for all the participants indicating a similar performance among participants. The path optimality ratio indicates that there was a low difference between the optimal path length and that performed by the participants (1.2 and 1.16 on average, respectively, for task 1 and task 2, i.e., an increase of 10%–20%). However, the time optimality factor indicates that was a large increase (5.4 and 2.75 on average, respectively, for task 1 and task 2, i.e., between three and five times more). This is due to the BCI time to develop the stimulation, recognize the command desired, and recover from BCI errors. No collisions occurred during the experiments because of the autonomous navigation system. From the BCI point of view, the interaction with the wheelchair was also satisfactory since the lowest performance of the pattern recognition system was 81%, and the mean performance was above 94%.

These results were very encouraging since the experiments were carried out in scenarios designed to evaluate maneuverability and navigation in open spaces and covered many of the typical real navigation situations of these devices.

2) Brain–Computer System: This evaluation was divided into an evaluation of the pattern recognition (BCI accuracy) and an evaluation of the graphical interface design. Some metrics were proposed to evaluate the accuracy of BCIs [35]. Based on them, the following measures were used in this study.



(Task 1) (Task 2)

Fig. 7. First row shows snapshots of the experiments with the wheelchair. The first two figures correspond with task 1, and the following two figures with task 2. The second row shows the map generated by the autonomous navigation system and the trajectory of the wheelchair in one real experiment of each task. Black zones indicate obstacles, white zones indicate known areas, and gray zones indicate unknown areas.

TABLE I
METRICS TO EVALUATE THE WHEELCHAIR PERFORMANCE

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
Task Success	1	1	1	0	1	1	1	0
Path length (m)	12.8	19.0	15.7	2.0	37.5	41.4	39.3	1.3
Time (s)	448	834	571	123	507	918	659	130
Path opt. ratio	1.07	1.59	1.20	0.06	1.10	1.22	1.16	0.02
Time opt. ratio	6	10	5.40	1.54	2	4	2.75	0.28
Collisions	0	0	0	0	0	0	0	0
Useful BCI acc.	0.88	1	0.95	0.04	0.81	1	0.94	0.07

TABLE II
METRICS TO EVALUATE THE PATTERN RECOGNITION STRATEGY

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
Real BCI accur.	0.85	1	0.93	0.05	0.77	1	0.92	0.07
Useful BCI accur.	0.88	1	0.95	0.04	0.81	1	0.94	0.07
# Total errors	0	4	1.6	1.35	0	7	1.9	2.13
# Useless errors	0	3	1.3	1.16	0	6	1.5	1.9
# Useful errors	0	1	0.3	0.48	0	1	0.4	0.52
Mission time (s)	53.8	64.2	59.4	2.9	63.1	80.8	72.1	5.6

1) *Real BCI accuracy:* ratio of BCI correct selections to total number of selections;
2) *Total errors:* number of total incorrect selections of the BCI;
3) *Useful errors:* incorrect selections of the BCI that the participant decided to reuse;
4) *Useless errors:* incorrect selections of the BCI that the participant decided not to reuse;
5) *Useful BCI accuracy:* ratio of good selections plus useful errors to total number of selections;
6) *Mission time:* mean time to accomplish one mission. The global navigation task is accomplished by iteratively setting navigation missions.

The results are summarized in Table II. The real accuracy was on average greater than 92%, which indicated a high accuracy. The standard deviation was low and very similar in both tasks, thus revealing a congruent and homogeneous behavior among the participants and tasks. There is a distinction between real and useful accuracy because in some situations, although the BCI system did not recognize the participant's selection, the BCI selection was used by the participant to achieve the task.[3] These BCI errors were referred to as useful errors, while the incorrect selections that were not reused were referred to as useless errors. Note that 20% of the errors in the tasks were useful for the participants, and thus, the useful accuracy was 94%, which was greater than the real accuracy. Furthermore, these errors did not increase the number or time taken to select and validate during a task.

Another error-related issue was that, although there were on average 1.3 and 1.5 useless errors, respectively, to task 1 and task 2, their effect was only a delay in the execution time until a new selection was made. During the experiments, the BCI system never set an incorrect mission for the autonomous navigation system. This was because the probability of the situation was below 0.3% (in the usage protocol, there must be a BCI failure

[3]This situation is common in open spaces. For example, in the situation displayed in Fig. 3(a), many goal locations in front of the vehicle could be used to navigate along the corridor.

TABLE III
METRICS TO EVALUATE THE GRAPHICAL INTERFACE

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
# 1st grid row	0	1	0.1	0.3	0	4	2.7	1.3
# 2nd grid row	0	4	1.7	1.1	1	10	4.3	2.8
# 3rd grid row	1	9	5.6	2.4	1	9	3.7	2.5
# Left arrow	0	2	1.1	0.6	0	1	0.1	0.3
# Right arrow	1	6	2.1	1.6	0	1	0.1	0.32
# Validations	8	14	9.6	1.9	7	12	9.2	1.9
Usability rate	2.0	2.4	2.1	0.1	2.0	2.6	2.2	0.2
# Misunderstandings	0	0	0	0	0	0	0	0

TABLE IV
METRICS TO EVALUATE THE NAVIGATION SYSTEM

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
Task success	1	1	1.00	0.00	1	1	1.00	0.00
# Missions	8	14	9.60	1.90	7	12	9.20	1.93
# Collisions	0	0	0.00	0.00	0	0	0.00	0.00
Path length (m)	12.84	19.02	15.74	1.99	37.52	41.44	39.31	1.33
Velocity (m/s)	0.10	0.15	0.13	0.01	0.16	0.19	0.18	0.01
Time in motion (s)	100	160	124.4	19	206	247	220	12
Clearance min (m)	0.67	0.88	0.79	0.07	0.47	0.71	0.61	0.07
Clearance mean (m)	2.83	3.16	3.02	0.12	3.19	3.34	3.28	0.05

in a selection first and then another BCI failure that results in the selection of the validation option).

The other aspect of the BCI was the design of the graphical interface used to achieve the navigation tasks. Some of the metrics proposed in [27] were adapted to assess the user's interfaces of intelligent wheelchairs. Based on them, the following measures were proposed.

1) *Command utility:* command usage frequency;
2) *Usability rate:* number of selections per mission;
3) *Misunderstandings:* number of errors by misunderstandings in the interface (they could arise due to a misunderstanding of the usage protocol or to a visual representation of the objects).

The results are summarized in Table III. In general, the design of the interface was enough to correctly use the system, since all the participants were able to operate it and carry out the navigation task. The command utility was greater than zero for all the participants and commands, thus indicating that they used all functionalities on the screen (there were no useless commands). The frequency of usage was highly dependent on the driving style, which will be analyzed in Section VI-B. Regarding the usability rate, the mean rate indicated very low extra selection rates (in theory, two selections per mission are needed). Note that this increase could come from BCI errors (see before) or from misunderstandings of the interface (affecting the interface design). Although there were no misunderstanding errors reported by the participants, the possibility that errors occurred but participants did not become aware of them could not be eliminated.

In summary, these results indicated that the pattern recognition strategy and the graphical interface of the BCI were suitable for controlling the intelligent wheelchair.

3) Navigation System Performance: There have been several metrics proposed to evaluate navigation of intelligent wheelchairs [27], [36]. The more representative ones for this case are as follows.

1) *Task success:* represents whether the participant completed the task successfully;
2) *Collisions:* number of collisions;
3) *Obstacle clearance:* minimum and mean distance to the obstacles;
4) *Number of missions*.

The results are summarized in Table IV. The performance of the navigation system was remarkable since all missions were successfully accomplished (all destinations were achieved without collisions). In total, the system carried out 188 missions, traveling a total of 550.5 m with an average velocity of 0.16 m/s (five times less than the usual human walking velocity). There were zero collisions during experimentation.

One of the main difficulties of current navigation systems is to avoid obstacles with safety margins and to drive the vehicle between close obstacles [30]. The mean minimum clearance was of 0.79 and 0.61, and the mean clearance was of 3.02 and 3.28, respectively, for task 1 and task 2, which indicated that the vehicle carried out obstacle avoidance with good safety margins.

One indicator of navigation performance is the adaptability to environments with different constraints, and another is the average velocity. In task 2 (open spaces), the average velocity was 0.18 m/s, which was greater than the average in task 1, i.e., 0.13 m/s. These measurements indicated that the navigation system adapted to the conditions of the environment, thus obtaining an increase in the average velocity in open spaces and a reduction when the maneuverability became more important.

In general, the navigation system successfully solved all the navigation missions without collisions in environments with different conditions and constraints (covering a wide range of real situations).

B. Users' Behavior

In this section, an evaluation of the participants' behavior is described while using the wheelchair. Three different but complementary points of view are focused on an execution analysis (to study what the participants did and their performance), an activity analysis (to study how the participants performed the tasks), and a psychological assessment (to study the participants' workload, learnability, and level of confidence). These three studies together will give a measure of the degree of accomplishment and adaptability of the wheelchair to the participants.

1) Execution Analysis: To measure the degree of accomplishment of the navigation task, the following metrics were used: 1) task success; 2) number of missions; 3) path length; 4) total time; and 5) useful BCI accuracy. These metrics were selected based on other studies [27], and the results are summarized in Table V. The results shown are the average of the two trials executed for each task. All the participants succeeded in carrying out all navigation tasks. The number of missions is an indicator of the intermediate steps required to execute and solve the complete navigation task. Participants 1, 2, and 5 needed fewer missions than the other participants, which showed an efficient mission selection for both types of navigational tasks.

TABLE V
TASK ACCOMPLISHMENT

	Task 1					Task 2				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
Task Success	1	1	1	1	1	1	1	1	1	1
# Missions	8.0	9.0	10.5	11.5	9.0	8.5	8.5	10.5	11.0	7.5
Path length (m)	14.9	16.6	17.9	15.8	13.6	39.3	40.0	38.2	40.9	38.2
Total time (s)	469	538	659	696	493	569	605	823	740	560
Useful BCI acc.	0.94	0.95	0.90	0.93	1.00	1.00	0.98	0.84	0.92	0.97

TABLE VI
METRICS FOR THE ACTIVITY ANALYSIS

	Task 1				Task 2			
	min	max	mean	std	min	max	mean	std
D_A	0.18	0.67	0.40	0.18	0.88	1.00	0.95	0.05
P_M (m)	1.44	1.90	1.68	0.20	3.71	5.12	4.44	0.66
T_M (s)	11.22	14.50	12.86	1.29	19.77	28.07	24.27	3.34
C_A	0.17	0.39	0.28	0.09	0.00	0.06	0.02	0.26
S_A	0.00	0.08	0.01	0.03	0.00	0.57	0.30	0.20

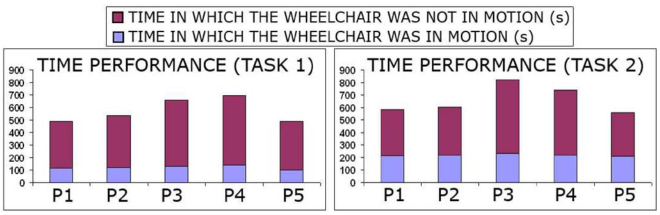


Fig. 8. Time (in seconds) in which the wheelchair was halted and time in which the wheelchair was in motion. The addition of these two terms is the total time taken to accomplish the task. These results are the mean of the two trials of each task executed.

Another metric for the individual navigation performance is the distance traveled. Participants 1 and 5 performed the circuits with a short path length and with the lowest number of missions. More interesting results were provided by the execution times of each participant since it involved a combination of BCI accuracy and efficient mission selection. On one hand, participants 1, 2, and 5 performed the tasks in less time than the others, thus showing the highest BCI performance and mission selection. On the other hand, participants 3 and 4 presented the lowest BCI accuracy and the most inefficient mission selection (many missions to solve the navigation task), thus having the longest navigation time. Furthermore, the great difference in time was due to the BCI accuracy (participants 3 and 4 showed the lowest performance) that led to a higher time to set a mission (see Fig. 8).

Based on the previous parameters, one can infer that there were two groups that explain how efficiently the participants used the system. The better mission selection with which participants 1, 2, and 5 performed the tasks reflected a more efficient use of the rehabilitation device. However, the results showed that participants 3 and 4 presented lower accuracy interaction with the wheelchair and higher number of missions, which suggested less efficient use than the others. The fact that all the participants succeeded in solving the navigation task and zero collisions occurred during the execution of both navigation tasks (see Table I) suggested a high robustness of the BCI-based wheelchair system, as well as adaptability to the potential users.

2) Activity Analysis: The activity analysis addresses the users' interaction strategy with the wheelchair in order to achieve navigation tasks. Following [37], there were two types of activity that apply to this context: the supervisory-oriented activity and the direct-control-oriented activity. Supervisory-oriented activity is defined fewer interventions and a selection of goals that explores the automation facilities, mainly trajectory planning and obstacle avoidance. This mode is characterized by more selections involving far goal destinations, a fewer left- and right-arrow selections, and fewer missions. Direct control activity is characterized by an increased user intervention and less confidence on the navigation capabilities of the system. This mode is operatively described by a higher number of selections on the arrow icons (to position the wheelchair), near range goal selections, and a higher number of missions.

The hypothesis is that the participants used different navigation styles to solve both navigation tasks. The metrics proposed in [27] were adapted to study the interaction strategy made by the participants during the execution of the navigation tasks.

1) Discriminant activity, which is denoted as D_A, measures the ratio of goal selections minus total of left and right turns to the total number of selections

$$D_A = \frac{\sharp\text{Dest.} - \sharp\text{Turns}}{\sharp\ \text{Selections}}. \quad (1)$$

2) Path length (in meters) per mission is denoted as P_M.
3) Time (in seconds) in which the wheelchair was in motion per mission is denoted as T_M.
4) Control activity descriptor, which is denoted as C_A, measures the ratio of turn selections to the total number of selections

$$C_A = \frac{\sharp\text{Turns}}{\sharp\text{Selections}}. \quad (2)$$

5) Supervisory activity descriptor, which is denoted as S_A, measures the ratio of first grid row destinations to the total number of selections

$$S_A = \frac{\sharp\text{1st Grid Row Dest.}}{\sharp\text{Selections}}. \quad (3)$$

The discriminant activity D_A, the path length per mission P_M, and the time in which the wheelchair is in motion per mission T_M are general metrics to differentiate between navigation styles. High values of these metrics indicate a supervisory-oriented activity, while low values indicate a control-oriented activity. Furthermore, the control-oriented activity is also characterized by high values of C_A, while supervisory activity is also characterized by high values of S_A. Table VI shows the results for these metrics. Values of D_A, P_M, and T_M were lower in task 1 than in task 2, which suggested a control activity during the first task and a supervisory activity during the second task. Furthermore, in task 1, the participants exhibited a tendency toward control activity, since C_A values were higher in comparison with values in task 2, while in task 2, the participants showed a tendency toward supervisory activity, since S_A values were higher in comparison with values in task 1. These results indicated that the participants used the two interaction strategies to solve the navigation tasks. The results also suggested that the participants

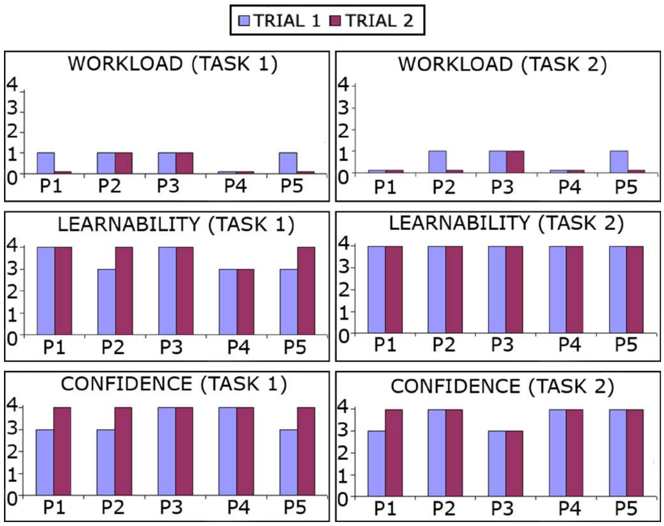


Fig. 9. Metrics used for the psychological assessment in two tasks. (a) and (b) Workload assessment on a scale of 0–4 (from almost no effort to considerable effort). (c) and (d) Learnability assessment on a scale of 0–4 (from difficult to easy to learn). (e) and (f) Level of confidence assessment on a scale of 0–4 (from least confident to highly confident).

had two mental models of the machine and switched between them to accomplish the maneuverability tasks or navigation in open spaces.

3) Psychological Assessment: This study consisted of a psychological test battery to study behavioral aspects such as workload, learnability, and level of confidence, which gave indications of the participants' adaptability to the rehabilitation device. The following metrics were used for this study.

1) *Workload based on effort:* This parameter measures the amount of effort and workload exerted by the participant.
2) *Learnability:* This parameter describes the ease of learning how to use the device during the navigation tasks.
3) *Level of confidence:* This parameter describes the confidence experienced by the participant during the navigation tasks.

The participants filled in questionnaires after the experiments to evaluate the previous metrics. The results are summarized in Fig. 9.

Regarding workload and effort, participants 2 and 3 reported more workload than the participants 1, 4, and 5. In general, all the participants reported more effort in task 1 than in task 2, probably because task 1 was more cognitive demanding in terms of planning the complex maneuvers. Participants 2, 4, and 5 experienced difficulties in learning to solve the first maneuverability task, but all showed a great improvement later. This could be explained by the fact that the first trial corresponded to the first time that they used the wheelchair to solve a predefined task. Because of performing always in first place the task 1, the learning is almost achieved during that task. This reason leads to the learning results shown during task 2, where all the participants selected the maximum value possible. Furthermore, the complex maneuvers performed on task 1 (which was considered more difficult than task 2) probably accentuated this fact. The results suggest that the participants had gradually learned to use the device. The last metric used was the level of confidence that the participant felt while operating the device. All the participants showed a great level of confidence, which was incremented during tasks except for participant 3. This could be due to his low performance in the execution of the tasks (due to the lowest BCI accuracy; see Table V). In general, there was always an improvement in all metrics; the participants experienced less effort, higher learning skills, and felt more confident, which reflected a high adaptability of the participants to the device.

TABLE VII
METRICS FOR THE VARIABILITY STUDY

TASK 1

	P1		P2		P3		P4		P5	
	Tr.1	Tr.2	Tr.1	Tr.2	Tr.1	Tr.2	Tr.1	Tr.2	Tr.1	Tr.2
Sel/min	2.15	2.20	2.21	2.00	2.21	2.16	2.23	2.15	2.23	2.14
Miss/min	1.01	1.03	1.01	1.00	0.93	0.98	1.01	0.97	1.12	1.07
Dist/min	1.86	1.94	1.44	2.36	1.62	1.64	1.16	1.66	1.43	1.93
Err/min	0.13	0.13	0.20	0.00	0.25	0.20	0.22	0.11	0.00	0.00

TASK 2

	P1		P2		P3		P4		P5	
	Tr.1	Tr.2	Tr.1	Tr.2	Tr.1	Tr.2	Tr.1	Tr.2	Tr.1	Tr.2
Sel/min	1.66	1.90	1.87	1.57	2.03	1.90	1.99	1.90	1.64	1.78
Miss/min	0.83	0.95	0.89	0.79	0.78	0.74	0.92	0.86	0.82	0.79
Dist/min	4.68	3.71	3.67	4.34	2.54	3.10	3.09	3.58	4.48	3.76
Err/min	0.00	0.00	0.09	0.00	0.39	0.25	0.15	0.17	0.00	0.10

TABLE VIII
INTRAUSER VARIABILITY

	P1	P2	P3	P4	P5
Variability Task 1	1.000	0.865	0.998	0.945	0.960
Variability Task 2	0.985	0.989	0.983	0.992	0.994

C. Variability Analysis

This study analyzed two types of variability degrees during the experimental sessions: intrauser and interuser. Intrauser variability measured the variability of a user among trials of the same task, whereas interuser variability measured the variability of execution among users during the execution of the same task. Within these results, the aim of this analysis was to measure the degree of homogeneity of the developed system (i.e., whether a homogeneous group of participants offered similar results in similar experimental conditions). The following metrics were defined for the variability study.

1) *Selections per minute:* number of selections per minute;
2) *Missions per minute:* number of missions per minute;
3) *Distance per minute:* effective distance traveled by the wheelchair per minute;
4) *Useless BCI errors per minute:* number of useless errors by the BCI system per minute.

The results are summarized in Table VII. To measure the variability, the Pearson's correlation coefficient was applied to the previously defined metrics; values close to one indicated low variability, while values far from one indicated high variability.

1) Intrauser Variability: The intrauser variability represented the degree of variability between the two trials executed for each participant in each task. These results are shown in Table VIII.

This coefficient was greater than 0.94 (except for participant 2 in task 1), indicating that the variability between trials was not substantial. This low intravariability denoted that the partic-

TABLE IX
INTERUSER VARIABILITY

	Task 1					Task 2				
	P1	P2	P3	P4	P5	P1	P2	P3	P4	P5
P1	1	0.962	0.987	0.953	0.981	1	0.960	0.917	0.953	0.998
P2	-	1	0.944	0.952	0.977	-	1	0.964	0.988	0.970
P3	-	-	1	0.978	0.980	-	-	1	0.990	0.926
P4	-	-	-	1	0.984	-	-	-	1	0.961
P5	-	-	-	-	1	-	-	-	-	1

ipants determined that their way to solve each task was correct, and therefore, they tried to perform equally in both executions.

2) Interuser Variability: It represented the degree of variability among participants in each navigation task. Results of this analysis are shown in Table IX. The coefficient was greater than 0.92, thus indicating a low intervariability. This low variability denoted that the users executed the task in a similar and analogous way. The inter- and intravariability results indicated that, under the same experimental conditions, the group performed similar actions, thus giving the system a high degree of homogeneity and invariability against different users in a variety of situations.

VII. CONCLUSION AND FUTURE WORK

This paper describes a new brain-actuated wheelchair concept that relies on a synchronous P300 BCI integrated with an autonomous navigation system. This concept gives the user the flexibility to use the device in unknown and evolving scenarios using the onboard sensors. Furthermore, once the user sets the destination, he/she can relax, thus avoiding exhausting mental processes.

The system was used and validated by five healthy participants in three consecutive steps: screening, virtual environment driving, and wheelchair driving sessions. During the real experiments, the system showed high performance and adaptability, since all participants accomplished two different tasks with relative ease. The experiments were carried out in settings designed to cover typical navigation situations, such as open spaces and complex maneuverability. The BCI accuracy, the performance of the graphical interface as well as the performance of the navigation system were high, thus indicating that the integration of these technologies was satisfactory. The variability study suggested that the results had a low variability, thus giving the system a high degree of homogeneity.

Currently, the researchers are working on the improvement of the system. To address the low information transfer rate, which is a common problem of all event-related potential approaches, a P300 continuous control of the system is being developed in an attempt to reduce the total time to solve the tasks. In order to address the synchronous operation, in which the user had to continuously concentrate on the task, an interesting improvement on which the researchers would like to work is the adoption of asynchronous P300 control to support an idle state, as given in [38]. Although the BCI accuracy was high (94%), the researchers are working on the integration of a BCI-based online error-detection system (which is a direction followed in many laboratories [39], [40]). Another direction that the researchers are exploring is the substitution of the virtual reconstruction displayed on the graphical interface by an augmented reality with real-time video in devices that are not colocated with the users, such as the brain teleoperation of a robot [41].

In future, it would also be important to perform experimental validation with potential users of the developed system. These users would be those who have lost almost all voluntary muscle control due to diseases such as ALS, spinal cord injury, or muscular dystrophy.

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