

A self-paced BCI with a collaborative controller for highly reliable wheelchair driving: experimental tests with physically disabled individuals

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Abstract—Brain-controlled wheelchairs (BCWs) are a promising solution for people with severe motor disabilities, who cannot use conventional interfaces. However, the low reliability of electroencephalographic signal decoding and the high user’s workload imposed by continuous control of a wheelchair requires effective approaches. In this paper, we propose a self-paced P300-based brain-computer interface (BCI) combined with dynamic time-window commands and a collaborative-controller. The self-paced approach allows users to switch between control and non-control states without requiring any additional task or mental strategy, while the dynamic time-window commands allow balancing the reliability and speed of the BCI. The collaborative controller, combining user’s intentions and navigation information, offers the possibility to navigate in complex environments and to improve the overall system reliability. The feasibility of the proposed approach and the impact of each system component (self-paced, dynamic time-window and collaborative controller) were systematically validated in a set of experiments conducted with seven able-bodied participants and 6 physically disabled participants steering a robotic wheelchair in real office-like environments. These 2 groups controlled the BCW with a final driving accuracy greater than 99%. Quantitative and subjective results, assessed through questionnaires, attest to the effectiveness of the proposed approach. Altogether, these findings contribute to improve the usability of BCWs and hence the potential for their use by target users in home settings.

Index Terms—Brain-computer interface (BCI), self-paced, dynamic time-window, collaborative control, robotic wheelchair, physically disabled, quantitative and subjective assessment.

I. INTRODUCTION

PEOPLE suffering from conditions that affect neuromuscular structures and functions tend to lose a significant degree of autonomy in daily living activities. Powered

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wheelchairs may help them to increase their levels of mobility and quality of life [1]. However, many of them become unable to use conventional interfaces, as a result of impairment severity or physical ability deterioration [2]. For those with severe motor impairments, brain-computer interfaces (BCIs) may be an alternative solution as it is possible to send commands through brain signals without requiring muscle activity [3], [4], [5], [6]. Yet, using a BCI to control a robotic wheelchair is a very challenging task because BCI has low transfer rates and limited accuracy [7]. Controlling a BCI system requires continuous and high levels of attention and focus, which imposes a high mental and physical workload that limits its usability. In turn, this workload can cause attention shifts and fatigue, resulting in even greater uncertainty in decoded brain commands. In the context of brain-controlled wheelchairs (BCWs) steered in real-world scenarios, the low reliability and rate of BCI commands can lead to disastrous safety consequences for the user and the system [8]. For this reason, when compared to other BCI applications such as spellers or games, BCWs require much higher reliability and general usability, which is only possible if they integrate an assistive navigation system (ANS) that perceives the wheelchair’s surroundings and performs suitable and smooth trajectories, considering the user intents. This can be accomplished by combining user and machine outputs in a so-called collaborative controller [9], [5], [10], [6], [11], allowing BCI commands, which encode high-level goals, to be provided at sparse intervals without the need for precise, low-level continuous steering.

The aforementioned collaborative approach may not yet be sufficient for effective use of a BCI because the user still needs to provide BCI commands in regular time-windows and has to be continuously focused, which is a mentally demanding task [12], [13], [10]. Self-paced control (also known as asynchronous control) provides the possibility for users to send BCI commands only when they wish to, at their own pace. This is therefore a very desirable feature, which can lead to less mental effort and more natural driving interaction [14], [5], [15], [6], [16], [17], [18]. To implement a self-paced BCI, the system must automatically recognize control and non-control states. In a state of non-control, it is understood that the user does not want to select any command.

Brain-controlled wheelchairs have been researched for more than one decade. They are mainly based on three neural mechanisms: motor imagery (MI) [5], [16], [18], steady-state visual evoked potential (SSVEP) [13], [10], [19], [11],

and P300 event-related potential (ERP) [12], [20], [6], [21]. Hybrid brain-actuated wheelchairs have also been proposed combining different neural mechanisms or combining brain signals with other physiological signals [14], [15], [22], [23], [17]. They may be used to increase the system reliability or to adapt to users functionality. For example, in [15] it is proposed the use of MI for selecting left, right, forward and backward commands, P300 and MI for acceleration or deceleration, and eye-blinking to issue stop commands. In [17], the asynchronous control is achieved based on a left-right motor imagery sequence and commands are selected through a P300-based interface. Most proposed BCI systems consider a fixed time interval to select the desired command, meaning that a fixed number of stimuli sequences (P300-based BCIs) or a fixed time-window (MI and SSVEP based BCIs) are required for decoding the user's intention [5], [22], [13], [10], [19], [6], [21]. The use of a dynamic time-window to issue BCI commands is also a desirable feature, as the speed of the system can be adjusted online to the user's performance, thereby increasing BCI accuracy, however very few have used this approach [20]. BCWs can use either high-level commands [22], [19], [6], [14], [16], [21], [23] or low-level commands [5], [13], [20], [10], [15]. The use of high-level commands requires the robot to be able to perform autonomously safe and effective navigation without user's aid (commands can be either global, such as 'kitchen', 'wc', or local, such as 'door', 'go-left'). With low-level commands, the user can steer the wheelchair with raw commands (e.g., 'forward', 'left', 'increase speed'). Although this approach is flexible, as the user can control any specific motion, it is highly demanding and almost impossible to use in real-world environments, even with a collaborative controller. So far, the reported experimental tests combining user's intent and context awareness in a collaborative controller have been conducted in very structured environments [14], [13], [4], [10], [19], [23], [11] or open spaces [22], and in semi-structured environments [12], [5], [15], [6], [16]. Moreover, just a few works report experiments conducted with motor impaired participants [21], [23]. For more extensive surveys comparing different BCWs approaches, please refer to [24] and [8].

The main goal of this work is to research ways to increase both the reliability and usability of BCWs, extending our previous work [6], which was focused on the robotic navigation system, and reported preliminary data of a self-paced BCI approach. In the current study, a new set of experiments was carried out including participants with severe motor disabilities. We propose a P300-based BCW that combines the previously developed collaborative controller with self-paced control and a new dynamic time command approach. The impact of each of the three aforementioned control modes on three dimensions of usability (reliability, workload, and naturalness) of the overall system is assessed through systematic tests. Our robotic platform - RobChair - was ergonomically adapted to be used by severely motor impaired participants. Several navigation tasks were carried out in real office-environment by a group of 6 individuals with severe motor disabilities and by a control group of 7 able-bodied participants. The effectiveness of the proposed methods

and approaches were assessed based on quantitative metrics, as well as on subjective questionnaires to assess user experience. The main contributions of the current study are: 1) proposal and validation of a new dynamic time-window approach for BCI commands based on the degree of the classifier's confidence, and its combination with the self-paced approach, that adjusts the BCI speed to the user's performance over time. To the best of our knowledge, very few works have used dynamic time-window methods in brain-actuated wheelchairs (and those used different approaches) and none have done so in a non-simulated environment [20]. This automatic adjustment decreases the users' performance fluctuations that may arise from changes in the users' attention, thus maintaining the most stable reliability naturally; 2) validation of a self-paced approach that frees the user from being continuously focused on the BCI. This is achieved through a non-control state that does not involve any additional task for the user, as he/she only has to be relaxed in a state of inattention. At the same time, the approach also tunes the rate of false positives, which is different from other P300-based brain-actuated wheelchair approaches. The proposed self-paced detector contributes to a natural BCI operation increasing the usability of the system; 3) combination of three impactful features in a single framework: self-paced control, dynamic adjustment of time-window commands and collaborative control, aiming at high overall reliability. This led to an overall performance greater than 99% without decreasing the BCI speed, which shows the feasibility of the approach in this application but which can be extended to other different contexts (e.g., predictive spellers); 4) validation of the BCW in a realistic office-like environment with severe physically disabled participants. This represents a contribution to the effective validation of BCI approaches, as most studies have validated their approaches only with healthy participants.

Both quantitative and subjective results clearly support the importance of the proposed overall solution. This work represents an important effort in improving and assessing the usability of BCWs, moving toward its potential use by target users.

II. EXPERIMENTAL DESIGN

A. Participants

This study comprises two groups of participants: 7 able-bodied users, referred to as Group I, and 6 participants with severe motor disabilities referred to as Group II (see Tables I and II). The study was ethically assessed and approved by the board of the Cerebral Palsy Association of Coimbra (APCC) and was conducted complying with the code of Ethics of the Declaration of Helsinki. Informed consent was obtained from all participants, explaining the aims of the study, their role as participants (e.g., voluntary participation) and the ethical commitments of the research team (e.g., data anonymization, guarantee of confidentiality). The sample of able-bodied users (S1-S7) was composed of students and researchers with ages between 21 and 32 years old, with a mean age of 23.7 years. Only one participant had previous experience with P300-based BCI and none had experience in driving a wheelchair. Table I

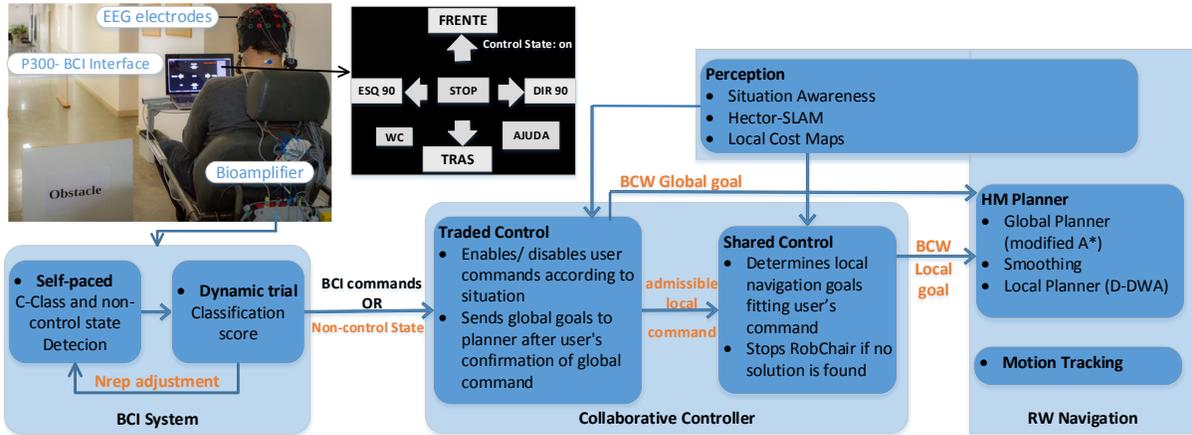


Fig. 1: Schematic representation of the overall BCW system, which is composed of three main modules: BCI System, Collaborative Controller, and Robotic Wheelchair Navigation.

TABLE I: Able-bodied participants

Subjects	S1	S2	S3	S4	S5	S6	S7
Age	32	25	22	22	21	21	23
Sex	F	F	M	M	M	M	M
BCI experience	YES	NO	NO	NO	NO	NO	NO

presents their ages, gender and their previous BCI experience. Group II (P1-P6) included outpatients from APCC with ages between 21 and 50 years old, averaging 37.5 years old. Primary clinical diagnoses for the latter group included cerebral palsy (2 cases), spinal cord injury (1 case), agenesis of the four members (1 case), limb-girdle muscular dystrophy (1 case) and Duchenne muscular dystrophy (1 case). Table II contains a more detailed description of the disabled participants, as well as a summary of their clinical and functional data. They were all dependent on human assistance in daily activities but still able to use powered wheelchairs independently with customized interfaces (even though some of them with great difficulty).

B. BCI Graphical User Interface and Commands

The BCI uses a visual oddball paradigm to evoke P300 event-related potentials. The visual paradigm comprises the following 7 steering commands: 'FORWARD', 'BACK', 'LEFT90', 'RIGHT90', 'STOP', 'WC', and 'HELP', in Portuguese ('FRENTE', 'TRAS', 'ESQ90', 'DIR90', 'STOP', 'WC', 'AJUDA', respectively), as depicted in Fig. 1. These symbols flash randomly with an highlight time of 100 ms and an inter-stimulus interval of 75 ms, resulting in a stimuli onset asynchrony (SOA) of 175 ms. For every round of the oddball paradigm each symbol is flashed once. An EEG data segment (epoch) with 256 time samples (one second) is extracted for each stimulus onset. Because of the low signal-to-noise ratio of P300 ERPs, several rounds are usually required to collect several target epochs, to improve the target classification.

For the conventional approach (here called as static trial) the number of repetitions/rounds (N_{rep}) necessary to select a target is fixed, settled according to the performance of

users in the calibration phase. For the dynamic trial approach (dynamic-time commands), the number of repetitions per trial during the online operation varies according to the target classification score. The overall trial time (TT) needed for symbol classification is computed from

$$TT = N_{rep} \times N_s \times SOA + CT \quad (1)$$

where $N_s = 7$ is the number of symbols, and $CT = 1$ is the time associated with the last flash of the trial. The Inter-Trial Interval (ITI), i.e. the time between each set of rounds, was set to one second.

C. Calibration sessions

Before starting the driving tasks, each participant performed a calibration session to obtain the classification models. Participants were seated in the RobChair with the computer screen positioned in front of them at a distance of approximately 30 cm, in the same conditions they have while driving the wheelchair. Participants were instructed to focus on the pre-defined target commands, successively provided at the top of the screen, and to mentally count whenever a target command flashes. Calibration consisted of a sequence of 9 symbols, and 9 rounds per symbol, collecting 81 target epochs and 486 non-target epochs, taking about 2 minutes. Participants performed only one calibration, from which all classification models and parameters were obtained to control the 3 performed tasks.

D. RobChair system

RobChair is a robotic wheelchair (RW) with differential actuation, equipped with optical encoders coupled to each motorized wheel and an Hokuyo UTM-30LX scan laser. Its navigation architecture is implemented in ROS and is composed of three main modules: perception, planning, and motion tracking. Currently, the perception module is composed of: situation awareness; Simultaneous Localization and Mapping (SLAM), performed with Hector-SLAM [25], and multi-resolution local cost maps, as described in [6]. The planning module is based on the hybrid motion (HM) planner, which is

TABLE II: Motor disabled participants

Subjects	Age	Gender	BCI ex- perience	Diagnosis	Type of dis- ability	Level of motor functionality	Interface used to steer powered wheelchair
P1	49	M	NO	CP (and sensory im- pairment)	congenital	Moderate autonomy in day-to-day ac- tivities. Upper and lower limbs with spasticity. Slight movements.	Joystick controlled by hand; Good efficiency.
P2	35	F	NO	Agenesis of the four members (and sen- sory impairment)	congenital	Moderate autonomy in day-to-day ac- tivities. Very small limbs; Slight move- ment disturbance.	Joystick controlled by stump; Good efficiency.
P3	50	M	NO	CP (and cognitive im- pairment)	congenital	Moderate autonomy in day-to-day ac- tivities. Upper and lower limbs with spasticity. Slight movements.	Joystick controlled by hand; Good efficiency.
P4	45	M	NO	SCI (and sensory im- pairment)	acquired	Head and upper limbs con- trol(tetraparesis). Moderate autonomy in day-to-day activities.	Joystick controlled by hand; Good efficiency.
P5	25	M	NO	Limb-girdle muscular dystrophy	congenital	Low autonomy in day-to-day activities. Proximal muscle weakness.	Joystick controlled by hand; Good efficiency.
P6	21	M	NO	Duchenne muscular dystrophy	congenital	Low autonomy in day-to-day activities. Muscle weakness.	Joystick controlled by hand; Good efficiency.

composed of a global planner based on a modified version of the A* algorithm, a smoother and a Double-Dynamic Window (D-DWA) approach for local planning. The collaborative controller is a decision-making module composed of two layers: traded and shared controllers (see Fig. 1). It receives sparsely issued high-level commands from the P300-based BCI that can either be global or local commands. Global commands consist of a set of target goals belonging to the navigational space (e.g. WC). As soon as a user selects a global command through the P300-based BCI, the traded controller is in charge of validating the command after user confirmation, sending it directly to the global planner. On the other hand, local commands allow the RW to navigate between local goals previously defined on the topological map (also referred to as decision points). A decision point is defined as an ambiguous place in the map because it allows several directions to be taken from there (e.g. intersections or bifurcations). In these situations, the user provides a direction through the P300-based BCI (e.g., FORWARD, BACK, etc.), and the collaborative controller determines the closest local goal in the direction provided by the user. Although these commands might be understood as low-level, they are, in fact, high-level commands because they provide a way to choose a pre-defined local goal. If the user issues a local command the traded controller enables/disables that command depending on the information provided by the situation awareness module (e.g. if a user issues the LEFT command but it is only possible to move forward, the command is disabled). The shared controller is in charge of determining the appropriate local navigation goal according to the admissible local command provided by the traded controller, situation, place being navigated, and topological map information (i.e. predefined subgoals or decision points). More details on the collaborative control algorithm can be found in [6]. RobChair was ergonomically adapted with help of APCC staff, to be used by severe motor impaired participants.

E. Navigation scenarios

The experiments consisted in steering the RobChair in a real indoor office environment. Participants performed three navi-

gation tasks as described below. The first task used the self-paced BCI with static trial time (STT), the second one used the self-paced BCI with dynamic trial time (DTT), and the third one used a non self-paced approach. The order of the tasks was the same for all participants, Task1-Task2 for the physically disabled participants and Task1-Task2-Task3 for the able-bodied group. Each participant performed the experiments on the same day. Before starting the task, each participant went through the designated path seated in the wheelchair, while an external operator was driving the wheelchair using a joystick, and the decision points were shown. Then, at the starting point of the route, after the calibration, each participant was enabled to become familiar with the interface, selecting commands, but with the wheelchair stopped. The familiarization time was variable between participants, ensuring that each one understood the task.

Task1 - Collaborative and self-paced control with STT.

Users steered the RobChair following the map route depicted in Fig. 2, from an office, represented as START, to a lab, represented as END using the self-paced P300-based BCI with STT, whose implementation is explained in section III-B. Before starting the tests, participants were instructed about the route, which included three narrow doorways (B, I, and K), two small obstacles (D and F) and two large obstacles (E and G). The minimum number of decisions to reach the final destination was 5, i.e. participants had to provide commands at each decision point (A, C, H, J, and L). However, the BCI is always outputting a command (target symbol or non-control state) at every trial. To detect the occurrence of false positives and false negatives, users were instructed to press an adapted switch whenever the BCI system selected an erroneous command, and someone was always behind for double checking.

Task2 - Collaborative and self-paced control with DTT:

The navigation task consisted of moving from the lab signed by START to the hall near the ELEVATOR, as shown on the map in Fig. 3, using the self-paced P300-based BCI with the DTT approach. This route included a room, passage through two doors and navigation in a corridor. To perform this



Fig. 2: Map with scenarios in which the participants performed Task1 and Task3 with 4 obstacles (D, F, E and G), 3 narrow passages (B, I and K) and 5 decision points (A, C, H, J and L).

navigation task, users were required to provide commands to start it and to choose the appropriate local goal in decision points (A, C, E, F, and H). As in STT, the BCI is always outputting a command (target symbol or non-control state) at every dynamic trial.

Task3 - Collaborative and non self-paced control with STT: In this task, we have evaluated the non-self-paced control in which the user had to provide a target selection at every trial, as in this mode the BCI could not detect the non-control state. The route was the same as in *Task1*, which consisted of going from OFFICE to LAB. RobChair’s speed was programmed to slow down at every decision point, that is, points in which the robot could not make a decision without an appropriate user command.

F. EEG Data Acquisition and Preprocessing

EEG was recorded with a 16-channel g.USBamp bioamplifier at positions Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz and Oz according to the international extended 10-20 standard system (see a photo of the system setup in Fig. 1). The reference electrode was placed at right or left earlobe and the ground at AFz. The EEG signals were acquired with active Ag/AgCl electrodes, sampled at 256 Hz, and filtered using a band-pass filter between 0.5 and 30 Hz and notch-filtered at 50 Hz.

III. METHODS: SELF-PACED P300-BASED BCI AND DYNAMIC TRIAL

A. Online Classification Pipeline

The online classification pipeline of the self-paced P300 BCI system is schematically represented in Fig. 4. After preprocessing, the data is segmented into epochs of 1 second, and then the epochs are normalized to zero mean and unitary standard deviation. The number of repetitions per trial is selected from the calibration session. Then, the normalized epochs of the N_{rep} repetitions are averaged for each channel and a feature extractor is applied, namely a statistical spatial filter (C-FMSB) that uses a suboptimum approach combining two criteria, the Fisher criterion (FC) and the SNR maximization (see details in [26]). Considering the averaged epochs $E_{N \times L}$, where $N = 12$ is the number of electrodes and

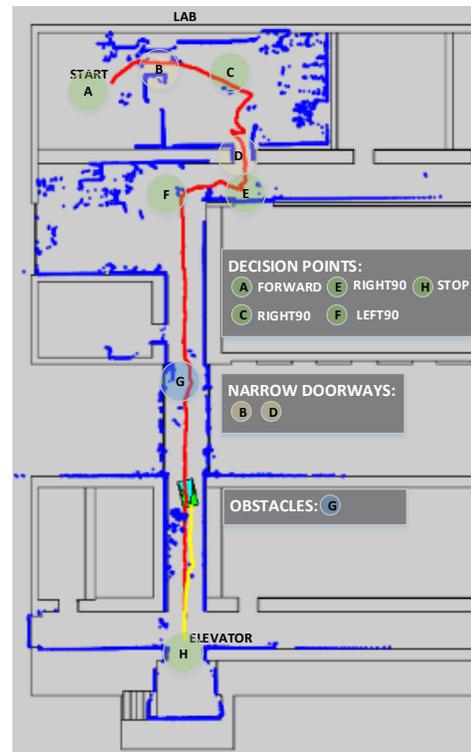


Fig. 3: Map with scenarios in which the participants performed Task2 with one obstacle (G), 2 narrow passages (B and D) and 5 decision points (A, C, E, F and H).

$L = 256$ is the number of samples, the spatial filter projection is obtained from

$$Z_{1:2} = W_{1:2}^T E \quad (2)$$

where $W_{1:2}$ are the 2 optimal filters that correspond to the eigenvectors associated with the largest eigenvalues obtained from the solution of the generalized eigenvalue decomposition using both FC criteria and Max-SNR. The resulting feature vector is the concatenation of the two projections, $V_{1 \times 2T} = [z_1 \ z_2]$, corresponding to 512 features. From these, the 120 most relevant features are selected using the R-square correlation method, leading to a feature vector $F_{1 \times 120}$. The feature

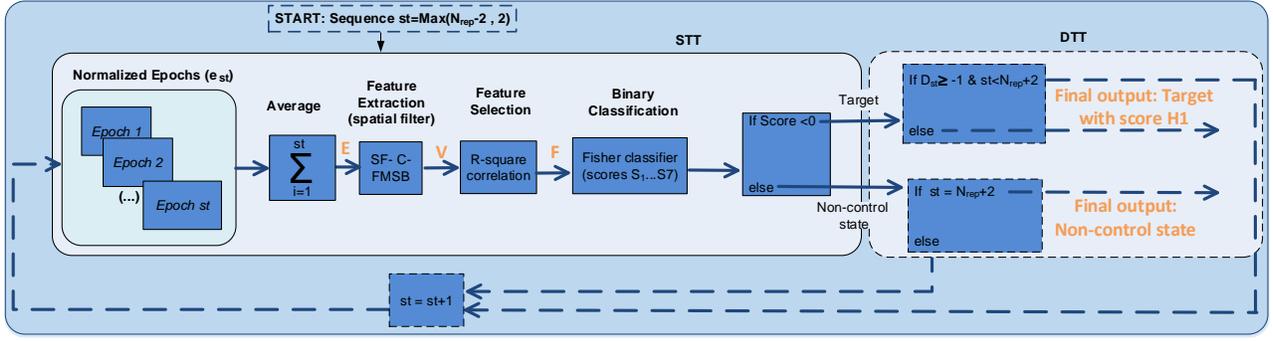


Fig. 4: Schematic representation of the overall pipeline of the self-paced P300-based BCI. Symbols E, V, F, and H1 refer to the averaged epochs, extracted features, selected features, and symbol with the highest score, respectively. Main solid line block represents the self-paced approach with STT. The dashed line blocks complement the STT block to implement the DTT approach (according to Algorithm 1).

vector is then classified by a Fisher Linear Discriminant (FLD) classifier, as described in sections III-B and III-C.

B. Self-Paced Mode

In self-paced mode, the BCI system needs to detect control and non-control states. The user can initiate his/her intention to enter the idle (non-control) state asynchronously whenever he/she wants, however, the system detection is made only at the end of each slot time (trial time). In the control state, participants were asked to focus on the target symbols, whilst in the non-control state (user has no intention of selecting a target), participants were asked to keep looking at the screen, but being relaxed without specifically attending to any of the symbols. This was thought as the most realistic scenario in those situations where the BCI is controlled by users unable to perform any motor movement. This scenario is different from most of the proposed P300-based BCWs that require a mental task to switch to the non-control state, for example, closing the eyes, performing mental tasks (e.g., reading a newspaper), selecting an extra symbol, or combining different neural mechanisms (e.g. P300 with motor imagery) [14], [15], [16], [17], [21]. The self-paced mode comprises 3 classes: target, non-target, and non-control state. Preliminary analyses, during which the calibration was performed with these three classes, showed that the epochs from the non-control class are very similar to non-target epochs, producing a similar classification score distribution as shown in the histogram of Fig. 5. Thus, the 3-class classification problem could be then transformed into a binary classification, and it was not necessary to consider the non-control state epochs to detect this class, nor to collect these epochs during calibration (we only need to collect target and non-target epochs). The Fisher classifier scores are positive for non-target and non-control epochs and negative for target epochs (the boundary is set to 0). However, the values of the scores depend on the threshold α , set for each participant, which adjusts the false positive rate as explained ahead, corresponding to virtually move the decision boundary (i.e., instead of moving the boundary, the scores are moved left or right according to the threshold).

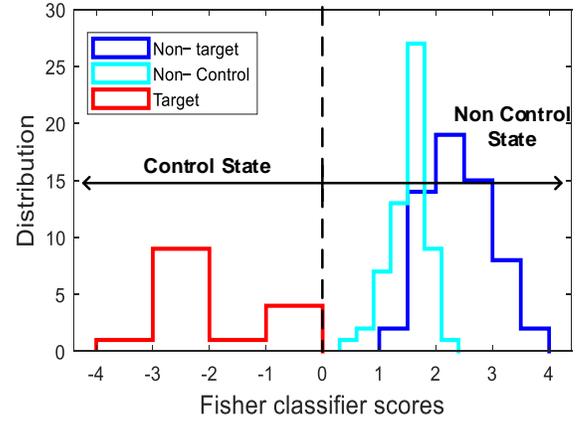


Fig. 5: Distribution (histogram) of FLD classifier scores of target, non-target, and non-control epochs obtained from a representative participant.

Considering the most discriminative features F_i from each class, where $i \in \{+, -\}$ (target (+) and non-target (-)), the FLD projection is obtained as

$$\mathbf{y}_i = w\mathbf{F}_i + \mathbf{b} \quad (3)$$

where w is the linear discriminative vector, and b is defined as

$$\mathbf{b} = -\frac{(b_1 + b_2)}{2} \quad (4)$$

with b_1 and b_2 computed from

$$\mathbf{b}_1 = \frac{1}{K_+} \sum_{k=1}^{K_+} \mathbf{Y}_+ + \sigma(\mathbf{Y}_+) \quad (5)$$

$$\mathbf{b}_2 = \frac{1}{K_-} \sum_{k=1}^{K_-} \mathbf{Y}_- - \alpha \times \sigma(\mathbf{Y}_-) \quad (6)$$

where K_i is the number of training samples in class i , σ is the standard deviation of target events and non-control state and α is a threshold that adjusts the false positive rate (FPR). False Positives (FP) occur when the user does not intend to

convey a command (non-control state) but the system detects a command. False Negatives (FN) occur when the user wants to provide a command but the systems detects a non-control state. The classifier is tuned to minimize the false positive rate (FPR) as it is considered that the impact of a false non-control state is better than a wrong command. FPs can lead to unwanted trajectories of the wheelchair which may render complicated to return to the desired destination goal (e.g., a unwanted 'BACK' command). Yet, when passing through decision points, FNs can also lead to unwanted navigation paths, but as the the wheelchair speed slows down at decisions points, the user has more than one chance to provide the desired command. The threshold α was set experimentally for each participant before the experiment, with increments of 0.25 within the interval $[1 : 0.25 : 3]$. Using the calibration data, the FPR and FNR are computed for each increment of α , and then the α that produces the lowest FPR and an FNR less than 10% is selected.

C. Dynamic Trial Approach

The DTT approach adjusts dynamically the number of repetitions to user's performance, balancing BCI speed and performance. Throughout the online operation, the P300 classification is computed for each sub-trial of index st . This value varies between $N_{rep} - 2$ and $N_{rep} + 2$ and its minimum value is limited to 2. N_{rep} is set in the calibration session matching a 90% offline classification accuracy (N_{rep} is the same for STT and DTT). The overall DTT approach is described in Algorithm 1 and schematically represented in Fig. 4. Starting with $st = \text{Max}(N_{rep} - 2, 2)$, the EEG signal is segmented into epochs, pre-processed and averaged. Features are then extracted, selected and classified using the models trained in the calibration session. A decision parameter D_{st} , that defines the desired degree of confidence to recognize the target command, is computed as the normalized difference between the symbol with the highest score (H_1) and second-highest score (H_2). If the D_{st} value is less than -1 (an empirical value set experimentally and the same for all participants), a valid prediction is identified, the classification output is the target with score H_1 , and the system proceeds to the next detection. Otherwise, there is a null prediction, that is, no target symbol is identified during the sequence st and the vector with epoch (E_{st}) is updated by adding the next epoch ($st = st + 1$). This procedure is repeated until a valid prediction is obtained or the number of sequences is equal to $N_{rep} + 2$.

D. Online metrics

We evaluate the feasibility of the BCI system through the accuracy (Acc_{BCI}), number of FP and FN (see definition in section III-B), and the number of wrong detected targets (WT). A WT occurs when the BCI detects correctly a control-state (the user is willing to send a command) but the selected target command is wrong (e.g., the user wants to issue a 'FORWARD' command and the BCI detects 'LEFT'). The BCI accuracy is defined as

$$Acc_{BCI} = \frac{Total_{com} - (FP + FN + WT)}{Total_{com}} \quad (7)$$

Algorithm 1 Dynamic trial time (DTT) algorithm.

- 1: E defines segmented epochs
 - 2: N_{rep} is set according to calibration data (P300 accuracy around 90%)
 - 3: Start with $st = \text{Max}(N_{rep} - 2, 2)$
 - 4: **while** $st \leq N_{rep} + 2$ **do**
 - 5: $E = 0$
 - 6: **for** $k = 1$ **to** $k = st$ **do**
 - 7: $E = E + E(k)$
 - 8: **end for**
 - 9: $E = \frac{E}{st}$
 - 10: $Z_{1:2} = W_{1:2}^T E$ (spatial filter projections)
 - 11: Apply feature selector
 - 12: Compute classification score (H_i) for each event applying FLD (eq. 3)
 - 13: Select the highest score (H_1) and the second highest score (H_2)
 - 14: $H_1 \equiv \max S_j, j \in \{1, \dots, N_s\}$
 - 15: $H_2 \equiv \max S_j, j \in \{1, \dots, N_s\} \setminus H_1$
 - 16: Compute the normalized difference between H_1 and H_2 :
 $D_{st} = \frac{H_2 - H_1}{H_1}$
 - 17: **if** $D_{st} < -1$ **then**
 - 18: 'Valid' prediction and the classification output is the target with score H_1 . The system is ready to proceed to the next detection
 - 19: **break**
 - 20: **else**
 - 21: 'Null' prediction, that is, no target symbol is identified during this sequence, so
 - 22: $st = st + 1$
 - 23: **end if**
 - 24: **end while**
-

where $Total_{com}$ is the total number of selections, i.e., the sum of the number of control commands (CC), i.e., target selections, and the number of non-control commands (NCC), i.e., trials in which the user does not want to select any target.

The global accuracy of the BCW is referred to as Acc_{BCW} and was computed taking into account the performance of the collaborative controller:

$$Acc_{BCW} = 1 - \frac{BCW_{err}}{CC + NCC} \quad (8)$$

where BCW_{err} is the number of the overall BCW errors, that is, the number of wrong commands at the output of the collaborative controller.

IV. EXPERIMENTAL RESULTS

The experiments were conducted with 7 able-bodied participants ($S1$ to $S7$) and 6 physically disabled participants ($P1$ to $P6$) described in Tables I and II. Participants of Group I performed the three navigation tasks, namely, $Task1$, $Task2$, $Task3$, and participants of Group II performed only $Task1$ and $Task2$. In $Task1$, it was used the self-paced control with STT approach (fixed number of repetitions, N_{rep}). In $Task2$, it was used the self-paced control with the DTT approach (number of repetitions was automatically adjusted

online to user's performance). The navigation time (from starting point to the final destination) took on average 11 and 8 minutes respectively for *Task1* and *Task2*. *Task3* ran in non-self-paced mode, taking on average 11 minutes. The overall experiment lasted between 2 hours and a half and 3 hours for the group I, and between 3 hours and 3 hours and a half for the group II, including setup, calibration, familiarization, navigation times, and questionnaires. Disabled participants did not perform *Task3* because the time allowed by their institution to carry out the experiments was not enough to accomplish all three tasks. On the other hand, the results of *Task3* obtained with Group I were very conclusive about the high difficulty and workload in using a non-self paced approach, so it was considered that this task would be unnecessary and unsuitable for the disabled participants. It should be stressed out that participants coming from APCC suffer from severe motor disabilities and required complicated transportation logistics to travel to the site of the experiments. Additionally, it was required that each participant was accompanied by a therapist or caregiver and a psychologist during the whole experimental process.

A. BCI performance

All commands received by the Hybrid Motion Planner of the RobChair result from the combination of the detected BCI command with the collaborative controller. Therefore, we need to assess both BCI accuracy (Acc_{BCI}) and "BCI + collaborative controller" accuracy (Acc_{BCW}) to analyze the impact of each module. The online results obtained for *Task1*, *Task2* and *Task3* are presented in Table III, Table IV and Table V. For Group I, the average BCI classification accuracies, calculated according to (7), are 97.1%, 94.5% and 89.1% for *Task1*, *Task2* and *Task3*, respectively. The number of commands provided by the users has been also calculated as it is one of the most important quantitative metrics to assess user effort and continuous workload. To accomplish *Task1*, participants in Group I needed to issue on average 10 control commands (target selections), while in *Task3* the same group issued on average 73 control commands (same path of *Task1*). Although in *Task1* only 5 decisions were necessary to reach the final destination, participants provided 5 extra commands on average due to wrong BCW commands or due to localization problems. For example, sometimes RobChair missidentified local deadlocks stopping, thereby requiring new commands from the user that led to a trajectory replanning. The self-paced mode used in *Task1* has clearly shown its effectiveness in considerably decreasing the number of control commands required to drive the RobChair. It is also possible to conclude that participants spent on average 86.3% of the time in a state of non-control, which undoubtedly greatly reduced the time that users were focused on target selection, with an expected positive impact on users' workload. The collaborative controller increased the overall accuracy of *Task1*, *Task2* and *Task3* by 2.9%, 4.5% and 5.5% respectively, reaching 100%, 99.1% and 94.6%, leading to a very high reliability of the overall system. None of the BCI errors made by Group I in *Task1* had an impact on the navigation as the

collaborative controller rejected them all. For Group II, BCI results were just slightly lower than for Group I, but the BCW accuracy was almost the same, as the collaborative controller corrected most of wrong BCI commands. These results show the effectiveness of the "Self-paced + collaborative" control approach, with performance remaining stable across patients with varied levels of physical disability.

TABLE III: Online performance for both groups in Task1: self-paced mode with static trial time

Subjects	CC	NCC	WT	FP	FN	BCW <i>err</i>	TT	Acc_{BCI} (%)	Acc_{BCW} (%)
S1	8	61	0	1	2	0	7.1	95.7	100.0
S2	12	72	0	0	2	0	5.9	97.6	100.0
S3	11	58	0	0	0	0	7.1	100.0	100.0
S4	10	78	0	0	0	0	7.1	100.0	100.0
S5	10	66	0	0	2	0	7.1	97.4	100.0
S6	7	57	0	0	2	0	8.4	96.9	100.0
S7	14	49	1	4	0	0	7.1	92.1	100.0
Average	10.3	63.0	0.1	0.7	1.1	0.0	7.1	97.1	100.0
P1	14	63	1	3	2	1	7.1	92.2	98.7
P2	23	104	1	5	1	0	7.1	94.5	100.0
P3	13	85	0	2	4	0	7.1	93.9	100.0
P4	13	68	0	3	4	1	7.1	91.4	98.8
P5	17	77	0	0	1	0	5.9	98.9	100.0
P6	12	66	0	2	0	0	7.1	97.4	100.0
Average	15.3	77.2	0.3	2.5	2.0	0.3	6.9	94.7	99.6

CC = number of control commands, NCC = number of non-control commands, WT = wrong targets, FP = False Positives, FN = False Negatives, BCW_{err} = number the BCW errors, TT = overall trial time, Acc_{BCI} is the BCI accuracy, Acc_{BCW} is the BCW accuracy.

The average number of FP and FN shown in Tables III and IV are respectively 1.1 and 0.7 for Group I, and 1.9 and 2.0 for Group II, showing that the control vs. non-control state detection is very effective. The comparison between the BCI accuracy obtained for *Task1* and *Task2* gives a measure of the impact of the DTT approach. The BCI classification accuracy was high but lower than using the STT (*Task1*), and the time to select a command was reduced in about 1 s for both groups (*paired t-test*, $p = 0.003$ and $p = 0.03$). This shows that the dynamic trial time can be used to adjust the BCI speed vs. accuracy. In order to favor accuracy, the DTT method should be more restrictive in the degree of confidence of the command (given by D_{st} in Algorithm 1).

B. Subjective questionnaires

Participants were asked to answer two questionnaires assessing their subjective perception of the performed tasks. The first questionnaire was based on the NASA-TLX [27] to assess mental demand, physical demand, temporal demand, performance, effort and frustration of the three tasks. Only one part of the NASA-TLX has been applied, that is, the participants rated each subscale but did not evaluate the contribution of each factor (weight). The overall workload for each subject is therefore an unweighted average of these six subscales. The second questionnaire was a customized questionnaire that compared the 3 tasks regarding the degree of user satisfaction, with questions directed to the specific tasks. The NASA-TLX workload scores range between 0 and 100 (21 graduations), while the customized questionnaire ranged

TABLE IV: Online performance for both groups in Task2: self-paced mode with dynamic trial time

Subjects	CC	NCC	WT	FP	FN	BCW _{err}	TT _{Max}	TT _{Min}	TT _{Mean}	Acc _{BCI} (%)	Acc _{BCW} (%)
S1	7	27	0	1	0	1	5.9	4.7	5.5	97.1	97.1
S2	11	31	0	0	0	0	8.4	3.5	4.9	100.0	100.0
S3	14	27	0	0	0	0	9.6	5.9	6.7	100.0	100.0
S4	10	31	0	1	0	0	5.9	4.7	5.8	97.6	100.0
S5	19	30	0	4	1	0	9.6	5.9	6.4	89.8	100.0
S6	10	23	0	1	1	0	10.8	5.9	8.0	93.9	100.0
S7	41	23	7	4	0	2	8.4	4.7	6.3	82.8	96.9
Average	16.0	27.4	1.0	1.6	0.3	0.4	8.4	5.0	6.2	94.5	99.1
P1	9	33	0	0	2	0	7.1	7.1	7.1	95.2	100.0
P2	36	36	5	6	2	1	9.6	4.7	6.8	81.9	98.6
P3	9	31	0	0	1	0	9.6	5.9	7.1	97.5	100.0
P4	12	79	0	1	4	1	5.9	4.7	5.7	94.5	98.9
P5	13	50	0	0	0	0	4.7	3.5	4.4	100.0	100.0
P6	8	31	1	1	3	0	7.4	5.2	6.2	87.2	100.0
Average	14.5	43.3	1.0	1.3	2.0	0.3	7.4	5.2	6.2	92.7	99.6

CC = number of control commands, NCC = number of non-control commands, WT = wrong targets, FP = False Positives, FN = False Negatives, BCW_{err} = number of BCW errors, TT_{Max} = maximum trial time, TT_{Min} = minimum overall trial time, TT_{Mean} = mean of trial time, Acc_{BCI} is the BCI accuracy, Acc_{BCW} is the BCW accuracy.

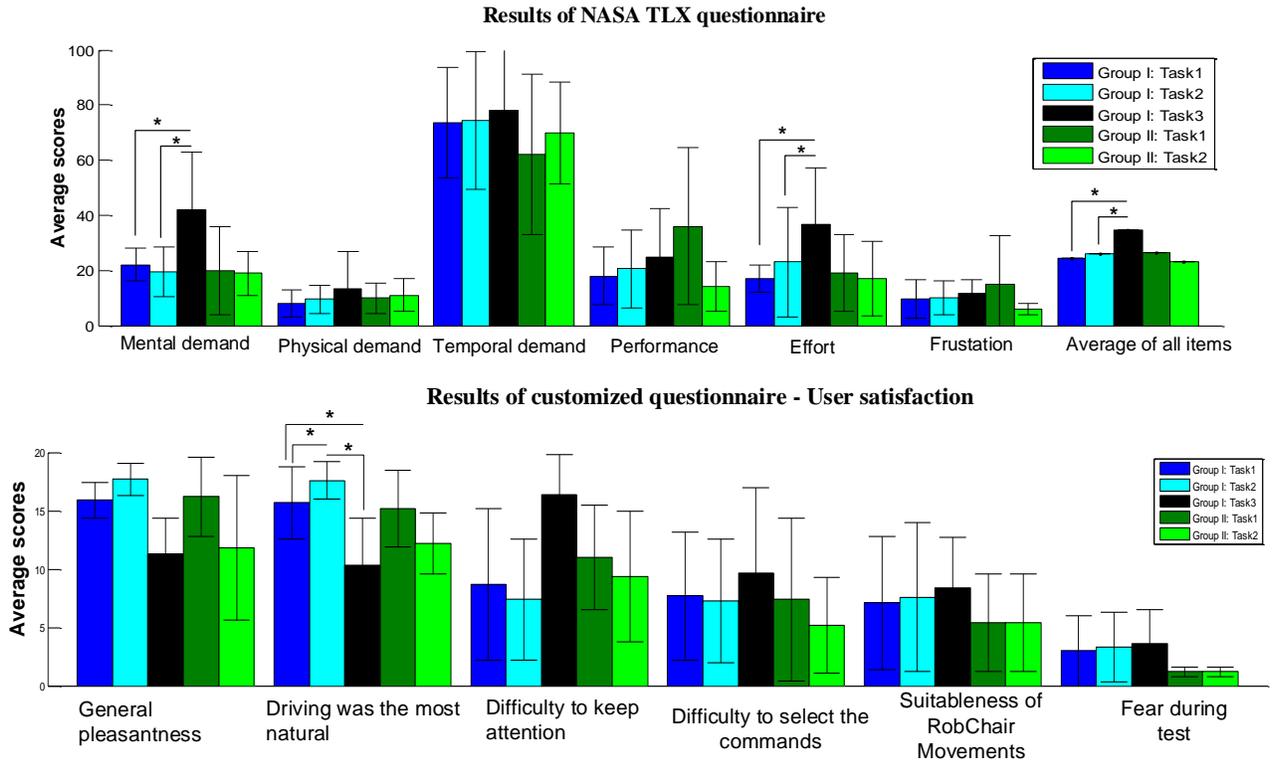


Fig. 6: Results of the questionnaires for each group. Top: NASA TLX raw rating scores and unweighted average of all items (scale 0-100); and Bottom: results of user-satisfaction customized questionnaire (scale 1-20). (*) indicates items that were statistically significant.

from 1 (very low) to 20 (very high). For the performance parameter, the scale is inverted, i.e., 1 is perfect and 20 is failure. In addition, psychometric questionnaires were applied to Group II to assess the emotional state according to State-Trait Anxiety Inventory (STAI) [28] and the Beck Depression Inventory (BDI) [29], in order to ensure that the participants were emotionally capable of performing the tasks.

The average results of the two subjective questionnaires are in Fig. 6. Group I reported mental demand and effort as significantly higher in *Task3*, compared to *Task1* (diff=20.0, paired t-test, $p=0.01$, and diff=19.5, $p=0.02$, respectively), and compared to *Task2* (diff=22.5, paired t-test, $p=0.006$, and diff=13.5, $p=0.002$, respectively), as expected from the quantitative results. *Task2* was scored as slightly less mental

TABLE V: Online Performance for healthy participants (Group I) in Task3: non self-paced mode with static trial-time

Subjects	CC	WT	BCW _{err}	TT	Acc _{BCI} (%)	Acc _{BCW} (%)
S1	85	21	10	7.1	75.3	88.2
S2	73	2	2	5.9	97.3	97.3
S3	65	4	4	7.1	93.8	93.8
S4	71	4	4	7.1	94.4	94.4
S5	85	7	3	7.1	91.8	96.5
S6	62	11	3	8.4	82.3	95.2
S7	71	8	2	7.1	88.7	97.2
Average	73.1	8.1	4.0	7.1	89.1	94.6

CC = number of control commands, NCC = number of non-control commands, WT = wrong targets, TT = overall trial time, Acc_{BCI} is the BCI accuracy, Acc_{BCW} is the BCW accuracy.

demanding than *Task1* for both groups (diff=2.5 and diff=1), but the difference is not statistically significant. The perceived performance of Group I in *Task1* was slightly greater than in *Task2* and *Task3*, although BCI classification accuracies of the 3 tasks were very similar. Group I classified *Task3* as more temporal demanding, without significant differences between tasks (paired t-test, $p=0.26$ and $p=0.35$). For Group I, temporal demand was similar for *Task1* and *Task2* (diff=1), and for Group II *Task2* was considered slightly less demanding (diff=8). The scores for physical demand and frustration of both groups are low (less than 3). These results suggest that participants felt comfortable and fearless. The average of Group I for NASA-TLX items shows that *Task3* was the task with the highest taskload (paired t-test, $p=0.03$ and $p=0.009$). For Group II, *Task2* presents the lower taskload, but the difference is not statistically significant. Comparative results between Task1 and Task2 could have been influenced by the difference between tasks. Although both tasks have the same number of decision points, Task2 has a shorter path and fewer obstacles (still, the participants issued more CC in Task2).

In the second questionnaire, *Task3* was reported as the less pleasant, less natural, more difficult to keep attention and the more difficult to select commands, which again corroborates the results of the quantitative metrics. Participants of Group I classified *Task2* as more natural than *Task1* ($p=0.03$). The difference in pleasantness between *Task1* and *Task2* was not statistically significant for both groups. Regarding the perception of "Suitableness of RobChair Movements", Group II considered the movements more appropriate than Group I.

V. DISCUSSION

A brain-controlled wheelchair is a complex system that requires a high level of reliability and safety and involves intelligent navigation systems. The goal of this study was to assess the impact of the combination of a collaborative controller with a self-paced control (using STT and DTT approaches) on users' effort, naturalness of interaction and system reliability when driving a robotic wheelchair with a BCI. Able-bodied and motor impaired participants used the proposed self-paced BCI with a mean accuracy of 95.8% and 93.7%, respectively. These results show the effectiveness of the

BCI classifier and in particular of the control vs. non-control state detection. Still, the average number of FP was higher than the number of FN, which was not what was intended. A posterior offline analysis made after the experiments showed that a better tuning of the threshold α could have decreased the number of false positives. The collaborative controller increased the overall system accuracy to above 99% for both groups, clearly showing its importance for the reliability of the BCW. Even using the non self-paced approach (which yielded a 89% BCI accuracy) the collaborative controller increased the overall BCW accuracy to 94.6%. The collaborative controller proved to have the desired effect, by discarding wrong BCI commands and replacing them by the intended ones, thereby reducing the impact of lower BCI performances. The self-paced control enormously reduced the number of the required commands, specifically from 73 to 10 on average. This reduction had a significant impact on the perceived overall task workload as shown in Fig. 6, in particular on mental demand and effort. Accordingly, the greater workload of the non self-paced operation was reflected in a decrease of the BCI accuracy in 8.0%, when compared to the self-paced operation. Analysing *Task1* vs. *Task2* it was found that the DTT increased the BCI speed by reducing the time per trial in about 1 sec, but it slightly decreased the BCI performance, which was not the desired outcome. Based on these results, we can state that the self-paced approach had a very high impact on the reliability, naturalness, and workload demand of the BCW, and the collaborative controller had a high impact on the reliability of the BCW, with increased relevance when the BCI performance was lower. Although with a lower impact on the entire system, the DTT approach showed the possibility of adjusting BCI speed vs. user's performance. This will be a subject of future research. For example, the D_{st} threshold should be individually tuned for each participant to ensure an improvement of the BCI accuracy. Moreover, the impact of the DTT approach may have been diminished by the high positive impact of the self-paced control, since the user is less susceptible to lack of attention and fatigue. Overall, participants scored *Task1* and *Task2* very similarly. As regards participants' subjective preference in performing the designated tasks, there were no significant differences between the two groups. The subjective results show a very positive user experience feedback regarding workload demand and naturalness of control of the overall system.

Table VI shows a comparison between different brain-actuated wheelchair architectures that are closely related to our system, i.e., that use a control scheme combining user and machine commands, a self-paced paradigm and experiments with real wheelchairs. Only one of the studies reported experiments with motor disabled participants [21], which emphasizes the need for more studies involving the potential target users, in a perspective of human-centred design. Additionally, most of the experiments of the proposed works were performed in highly structured environments set up in lab. Our work presents the most complex navigation scenario including both healthy and severely motor disabled participants. To the best of our knowledge our proposal is the only one achieving an overall accuracy greater than 99%, which validates the

TABLE VI: Summary of related BCW works that use a collaborative control, a self-paced paradigm and experiments with real wheelchair.

Study	BCI approach	Self-paced paradigm	Environment	Subjects
Rebsamen et al. [14]	P300 and MI	Static trial	Structured environment based on corridors and rooms without obstacles.	Healthy: 5
Carlson and Millan [5]	MI	Static trial	Unstructured environment based on an office room with static obstacles.	Healthy: 4
Wang al. [15]	MI and P300 and blink	Static trial	Semi-structured environment based on corridors with static obstacles.	Healthy: 4
Zhang al. [16]	MI or P300	Static trial	Semi-structured environment based on a domestic room with static obstacles.	Healthy: 9
He al. [21]	P300	Static trial	Real. Trajectory with two destinations in a room.	Healthy: 8; Disabled: 5
Our study	P300	Static and Dynamic trial	Semi-structured environment based on office rooms and corridors with static obstacles and narrow passages.	Healthy: 7; Disabled: 6

proposed BCI and navigation approaches. Moreover, from this group of studies our study is the only one assessing user experience through subjective questionnaires.

Users steered the wheelchair in office-like environments requiring challenging tasks, such as narrow door passages and obstacle (static and dynamic) avoidance. Although complex, the scenarios were still very controlled and different from users' daily home settings. The experimental procedures were also very controlled, as the research team was always assisting the tasks. The good results achieved by motor disabled participants suggests that the proposed BCI may represent an effective solution for wheelchair control. The overall results have been very promising and motivate new further research already under way, namely the integration of vision sensors to recognize semantic features, such as doors, tables, chairs, which will be incorporated dynamically as target goals in the interface. Error-related potentials (ErrP) that we have already used in a different context [30] are also being integrated to improve the reliability of the BCI commands.

VI. CONCLUSION

This study assessed the impact of the integration of collaborative control, self-paced control, and dynamic-time commands into a BCW system. The system was validated by 7 healthy participants and 6 motor disabled patients in real office-environment navigation tasks. Both able-bodied and motor disabled participants successfully controlled the BCI system with an average BCI accuracy of 95.8% and 93.7% respectively and the collaborative controller corrected most of wrong commands increasing the accuracy to more than 99% for both groups. The subjective results corroborate the quantitative results, showing a positive impact of self-paced and collaborative control. These results are promising for the effective and tailored use of BCWs by individuals with severe motor impairments. Still, more extensive experiments with a wider group of participants and in more natural living contexts are needed to validate the approaches.

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