# A Brain Controlled Wheelchair to Navigate in Familiar Environments

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***Abstract*—While brain–computer interfaces (BCIs) can provide communication to people who are locked-in, they suffer from a very low information transfer rate. Further, using a BCI requires a concentration effort and using it continuously can be tiring. The brain controlled wheelchair (BCW) described in this paper aims at providing mobility to BCI users despite these limitations, in a safe and efficient way. Using a slow but reliable P300 based BCI, the user selects a destination amongst a list of predefined locations. While the wheelchair moves on virtual guiding paths ensuring smooth, safe, and predictable trajectories, the user can stop the wheelchair by using a faster BCI. Experiments with nondisabled subjects demonstrated the efficiency of this strategy. Brain control was not affected when the wheelchair was in motion, and the BCW enabled the users to move to various locations in less time and with significantly less control effort than other control strategies proposed in the literature.**

***Index Terms*—Brain–computer interface (BCI), P300, wheelchair.**

## I. Introduction

THE brain controlled wheelchair (BCW) described in this paper was designed to provide mobility to individuals who have lost most voluntary muscle control, but who are able to use a bain–computer interface (BCI). However, BCIs typically suffer from a very low information transfer rate. This means that either the uncertainty on the command will be high, or the time between consecutive commands will be large, i.e., several seconds. Can such a low bandwidth signal be used to safely and efficiently control a wheelchair, which requires specifying linear and angular velocities in real-time? This is the challenge we addressed in the BCW [1], which this paper tests and compares with existing brain controlled wheelchairs.

To let individuals who are severely disabled move to desired locations, a robotic wheelchair must fulfil the following conditions.

- It must be *safe*, since it transports a particularly vulnerable person.
- The control must be *ergonomic*: the wheelchair should provide efficient and intuitive navigation with as little (mental) effort as possible. Using a BCI requires concentration which can cause fatigue and using it continuously is tiring. This was observed in one of our experiments with a P300-based speller and people with severe disabilities, and was separately reported in [2]–[4]. Hence the control of the BCW must be as easy as possible, yet allow certain freedom to the user, such as stopping or changing course during motion. Moreover, the trajectory should be smooth and correspond to the user's understanding of a trajectory.
- Cost generally is the first factor mentioned by end users and physiotherapists. Therefore, the wheelchair should be *low cost*, in the sense that the customization of a conventional wheelchair should be minimal, so that people who need it can afford it.

Tanaka *et al.* [6] developed probably the first brain controlled wheelchair. A discrete approach was used to the navigation problem, in which the environment is discretized in 1 $\mathrm{m}^2$ squares, and the user decides where to move next by imagining left or right limb movements. A similar principle was used in the sophisticated wheelchair system recently developed by Iturrate *et al.* [7], where a virtual reconstruction of the surrounding environment (as inferred from laser range scanner data) is displayed. A set of points in the free space is presented, that can be selected using a P300 BCI, and these short term goals are reached automatically. However, the large number of steps required to reach a destination with these two systems might exhaust the subjects. For instance, Iturrate *et al.* report that it took 11 minutes and nine decision steps to realise a 40-m-long path with this system [7].

Millán *et al.* [8] proposed to use a BCI continuously analyzing the user's EEG to detect mental states associated with "forward," "left," and "right" commands which the robotic wheelchair executes while avoiding obstacles. The user is required to provide continuous commands during the motion, which may be tiring. Further, wrongly detected commands and conflicts with the autonomous controller, possibly leading to unwanted moves, may stress the user.

The alternative strategy we propose to control the BCW relies on a slow but safe and accurate P300 EEG brain interface, which allows the user to select an item in a menu with high confidence (see Fig. 1). Strategic locations in a known environment are predetermined. These are typical locations where the user usually goes to, e.g., living room (with the TV), kitchen, toilet, and bedroom. In order to simplify motion control, the wheel-

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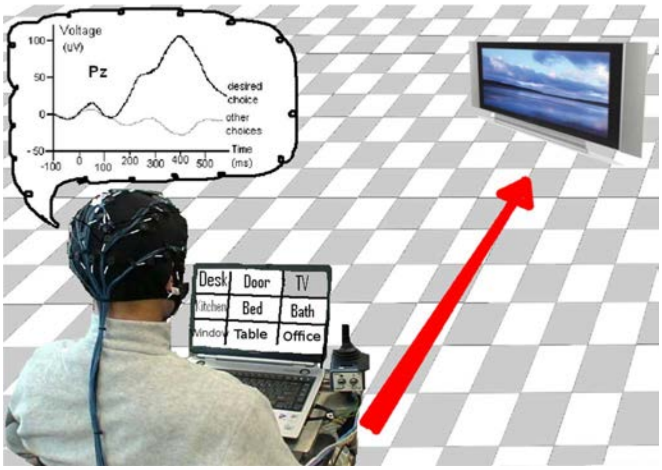


Fig. 1. Overview of the BCW: the user selects the destination (here the TV) using the P300 BCI and the wheelchair follows a guiding path to it. On the laptop's monitor is the menu where items are flashed randomly. If the user focuses his attention on an item, the EEG signal will present a peak around 300 ms after the target has been flashed (sketch adapted from [5]), which determines the destination.

chair is constrained along paths predefined in software joining the selected locations.

With this strategy the control of the wheelchair is reduced to the selection of appropriate destinations thus requiring minimum effort from the user. Since guiding paths are software defined and not hard coded, they can be easily modified if the environment changes [9]. To allow the user to stop the wheelchair during motion, two faster BCIs are proposed: one based on a fast P300 algorithm with only one item, the other on motor imagery ($\mu/\beta$-BCI).

The paper is organized as follows. Section II describes the BCW and the control strategy, and Section III the evaluation of the P300 BCI for destination selection performed with five healthy subjects. Section IV presents the fast P300 BCI algorithm and the $\mu/\beta$-BCI used for stopping, and evaluation results. Section V compares our BCW with other brain controlled wheelchairs.

## II. Principle of the BCW

### A. Motion Guidance Provides Driving Assistance

Using a slow user interface for controlling the wheelchair requires equipping it with some autonomy. We therefore decided to use a control strategy based on supervision by the user rather than by sensor based reasoning. The environment is represented as a graph containing nodes representing locations of interest, linked by virtual paths designed beforehand automatically or by a human helper, which can be flexibly modified as needed when the environment changes. The wheelchair follows those guiding paths using a dedicated controller [10].

This simple, adaptable motion control strategy is motivated by several reasons. In our opinion, state of the art autonomous mobile robots are not safe enough to transport a person who will not be able to press the emergency stop button fast, therefore semi-automatic motion is necessited. Also, dealing with the complexity of real world situations requires equipping such autonomous mobile robots with an array of sensors, which makes the wheelchair system more expensive. Further, decisions taken by autonomous systems may be felt as awkward and stress the user [9], [11]. Finally, people affected by motor disabilities still want to be in charge of their movements as much as possible, as in our motion control.

Our strategy, however, has two drawbacks. First, the system can only be used in an environment where paths are defined, and only predefined locations can be reached. Second, when modifications in the environments occur (such as changes in furniture location), the guiding paths must be updated accordingly. However, we believe that this is a solution especially attractive to people who are locked-in, providing just the mobility they can control, and modifications of the paths can be performed by caregivers who have performed changes in the environment.

### B. P300 BCI for Destination Selection

Selecting a destination from a list of predefined locations is similar to selecting letters in the alphabet. P300-based BCIs [12]–[17] have proved very successful with spelling devices as they allow selecting from a list of up to several dozens of items with reasonable time (typically 10–20 s) and great accuracy (i.e., above 95%). In contrast, faster BCIs such as those based on motor imagery [5] or mental task classification [18] enable choosing between only two or three possibilities. Besides, using a P300 BCI requires no training, the performances are stable over time, and can be used by people with severe disabilities, including people suffering from ALS [19].

In our setup, nine destinations are displayed on screen in a $3\times3$ matrix (see Fig. 1), and flashed in a random order. To select an item, the user focuses his or her attention on it; a simple way for focusing is to count the number of times the target is flashed. Around 300 ms after the target is presented, a peak appears in the EEG signal (see Fig. 1), and the target can be determined as the stimulus that occurred 300 ms earlier.

The algorithm used for P300 detection [17] works as follows. EEG signal is first cleaned from artefacts, filtered and downsampled. The resulting signal is then segmented into *epochs* from 100 to 500 ms after the onset of a button flashing. The result as well as its dynamic features form a feature vector which is fed to a support vector machine algorithm (SVM) for classification.

Each epoch is then assigned a score computed from the SVM's output and representing the confidence that it contains a P300 signal. The last eight scores for each item are averaged, and the item with the highest score is selected if its score is higher than a decision threshold.

The menu displayed on the interface is *context dependent*: only the locations connected to the current position by a guiding path are listed. Upon selection of a destination on the interface, the wheelchair starts heading toward it. This enables subjects to reach their goals efficiently and in a reasonable time.

### C. Faster BCIs for Stopping

The P300 interface used for destination selection is too slow to be used to stop the wheelchair during motion; a BCI with a shorter response time is required. The system switches between the fast and slow BCIs depending on the state of the wheelchair: when stopped the destination selection interface is pre-

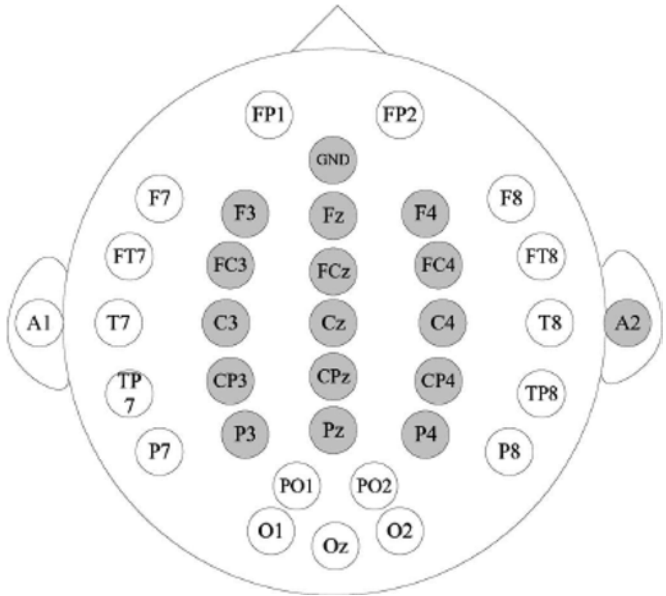


Fig. 2. Placements of the 15 electrodes used in our experiment (plus reference and ground points) in shade.

sented, whereas while in motion the fast BCI for stopping is used. We have tested two possible BCIs for stopping: a faster version of the P300 interface used for destination selection, and a BCI based on motor imagery. Both allow to issue a stop command within five seconds (see Section IV).

### D. BCW Prototype

The robotic wheelchair used for our BCW, described in [20], is built on a Yamaha JW-I power wheelchair. Sensors are limited to two optical rotary encoders attached to glide-wheels used for odometry, a bar code scanner for global positioning, and a simple proximity sensor mounted in front of the wheelchair to avoid collisions. When an obstacle is detected within 50 cm, the wheelchair stops to avoid collision. The interface switches then back to the destination selection menu, from which the user can resume motion if the obstacle is moving away, or choose an alternative route or destination.

Compared to BCWs using a laser range scanner or other complex sensors [7], [8], the BCW requires fewer and much cheaper sensors, and fewer modifications of a user's wheelchair.

A laptop with a DAQ card runs the path following controller [1], [10], [21] and drives the wheelchair. This controller communicates with the BCI process: it sends the commands to be displayed on the interface and receives the user's selection. In our experiments, the scalp EEG signal was acquired using a NuAmps device from Neuroscan Inc. The EEG was recorded at 250 Hz from 15 Ag/AgCl electrodes placed above the inferior frontal, central, and parietal regions of the cortex, as shown in Fig. 2.

## III. Evaluation of the P300 Interface for Destination Selection

We define the following parameters to analyze the performance of the BCIs.

- The *response time* (RT) is the interval from the time the user initiates the control to the time the command is issued. Note that the measure of RT encompasses the true positive and false negative rates due to our moving average window based algorithm: if a P300 epoch is misclassified, more time is required for the selection.
- The *false activation rate* (FA) is the number of times per minute that a command is issued when the subject is not intending to activate the interface. While unintended activations are often expressed in the percentage samples that are false positives, expressing unintended activations per minute using the FA is more suitable for a time-critical application, such as the control of our wheelchair.
- The *error rate* (Err) is the ratio of wrongly selected targets divided by the total number of selections during an experiment, expressed in percentage. This measure does not take into account selections due to false positives.

### A. Data Collection for Static Analysis

To conduct analysis of our P300 interface we collected EEG data from five subjects (subjects 1–5), all males between 22 to 36 years without known pathology. Note that no subject screening was conducted. The experiments were approved by the institutional review board of the National University of Singapore.

The interface used for presenting the stimuli was a $3\times3$ matrix as illustrated in Fig. 1. Buttons were flashed one after the other round by round, where a *round* is a random sequence of the nine buttons. Flash duration was 100 ms with an inter-flash interval of 10 ms, thus one round took 990 ms. Data collection was performed in a single session during which control and noncontrol tasks were interleaved, with a break of 2 min in between two tasks. The subjects were guided through the tasks by an interactive program indicating on the monitor when to rest and what button to focus on.

In the control task, the subject was asked to focus on the interface. The control task was divided into four sections. In Sections 1–3, the subject attended to one button (the target) for eight rounds, paused 2 s, and moved on to the next button until he/she had gone through all the nine buttons. Each round yielded one epoch of target data corresponding to when the target button was flashed and which should contain a P300 signal, and eight epochs of nontarget data corresponding to when the other buttons were flashed. Each of these three sections hence contained 72 ($9\times8$) epochs of target data and 576 ($9\times8\times8$) epochs of nontarget data. These three sections were used to train the SVM. The setting of the fourth section was the same as that of the first three, except that the subject had to attend to the targets for 50 rounds instead of eight. Hence the fourth section contained 450 epochs of target data and 3600 epochs of nontarget data. Data from this section was used to evaluate the trained SVM.

In the noncontrol task, the subject paid no attention to any button nor to the computer display. It was divided in three sections of 50 rounds, corresponding to 4050 ($50\times9\times9$) epochs of noncontrol EEG data per section. In the first section, the subject was reading a newspaper. In the second one the subject was relaxed with closed eyes. In the third one the subject was given a question sheet including a few arithmetic tasks, and needed to

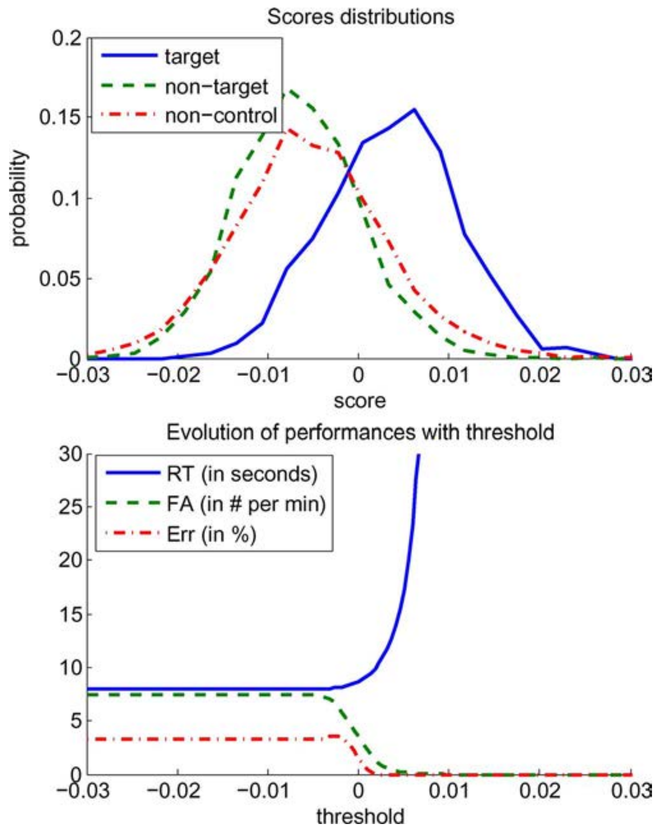


Fig. 3. Results of the P300 BCI evaluation for a typical subject. Top: distributions (PDF) of scores for target, nontarget, and noncontrol epochs. Bottom: RT, Err, and FA for different values of the decision threshold. Note that a single ordinate is used to represent the three different units.

finish the tasks quickly. No significant difference was found in the behavior with these three conditions, which were thus combined in the subsequent analysis, yielding 12 150 epochs.

According to the timing scheme mentioned before, the eight rounds tasks took approximately 1 min and the 50 rounds tasks 8 min. So the data collection on each subject ran for approximately 30 min, excluding the EEG preparation time.

## B. Results

Top panel of Fig. 3 shows the score distribution for the target, nontarget, and noncontrol epochs. The three distributions are approximately normal, as revealed by the Kolmogorov–Smirnov test ($p$-values are 0.83, 0.15, 0.13, respectively). There is no significant difference between the means of the nontarget and the noncontrol distributions (Cohen's $d$ effect size is 0.12) but there is a significant difference between the mean of the target distribution and the mean of the nontarget and the noncontrol distributions (Cohen's $d$ effect size is 1.23).

Bottom panel of Fig. 3 shows RT, Err, and FA for different values of the decision threshold. RT increases with the threshold: there are less epochs with a high score, therefore it takes a longer time until one of the scores reaches the threshold. Conversely, FA is high for low threshold values, and tends to zero for high values. The maximum possible value for FA is $60/8 = 7.5$ since scores are averaged over the last eight rounds. Err is below 5% and decreases for large values of the threshold.

TABLE I
OPTIMUM PERFORMANCES

| Subject | RT (s) | FA | Err (%) |
|---|---|---|---|
| 1 | 12.3 $\pm$ 5.4 | 0.7 | 0.15 |
| 2 | 17.3 $\pm$ 8.2 | 1.0 | 0.11 |
| 3 | 13.9 $\pm$ 5.6 | 0.7 | 0.09 |
| 4 | 18.4 $\pm$ 8.7 | 0.7 | 0.14 |
| 5 | 21.7 $\pm$ 9.1 | 1.1 | 0.13 |
| average | 15.4 $\pm$ 6.8 | 0.7 | 0.12 |

A good destination selection will be obtained with low error and low false activation rates. In order to ensure this, the best threshold value was selected, for each subject, so as to minimize the following cost function:

$$C = \frac{\mathrm{RT}}{[\mathrm{RT}]} + \frac{\mathrm{FA}}{[\mathrm{FA}]} + \frac{\mathrm{Err}}{[\mathrm{Err}]} \tag{1}$$

where the selected normalization factors $[\mathrm{RT}] = 10$ s, $[\mathrm{FA}] = 1/60$ s and $[\mathrm{Err}] = 0.1\%$, corresponding to typical values obtained during preliminary performance, ensure a balance between the three terms. Table I gives the resulting optimum performances for each subject as well as the average performances.

The optimal value of the threshold varies slightly from trial to trial, due to changes in the electrodes placement and in the user's cognitive state. Therefore, a quick calibration is required before using the interface. Calibration consists in recording a few data using an automatic protocol, training of the SVM, and searching the optimal threshold using the above cost function. Following the data collection protocol above, this requires recording two eight round sessions of control task and one 50 round session of noncontrol task, which takes approximately 10 min.

## C. Locking the Interface

As the FA rate is not zero, the interface is expected to generate random commands while the user is not using it. However, in a daily usage, the user would normally spend large amount of time not using the interface, for instance when resting, or performing another activity. In this case, the wheelchair could start moving to a random destination once every 85 s on average (as FA $=$ 0.7).

To prevent this, we implemented an interface scheme similar to the keyboard locking facility on cellular phones: the interface is locked by selecting the lock button twice. Once locked, no command can be issued before a sequence of keys is entered. Using a key sequence of three characters $(N = 3)$ and assuming FA $= 0.6/\mathrm{min}$, the false unlocking rate is $8.10^{-4}/\mathrm{min}$, or once every 20 h.

## D. Evaluation With the Wheelchair

Navigation experiments were conducted in a part of our lab building including five floors connected by a lift. We emulated a smart environment where the lift communicates with the wheelchair by manually operating the lift. At each floor, four destinations were interrelated by six guiding paths, which were designed prior to the experiment.

Our five subjects were asked to navigate between ten pairs of locations. All locations were on a different floor, hence three selections were required to reach the destination (30 selections per subject in total). All subjects succeeded at their first trial to reach all of the desired locations, taking an average of 15 s ($\sigma = 2.4$) to issue a command, and no wrong command was selected ($\mathrm{Err} = 0\%$).

## IV. Evaluation of the BCIs Used for Stopping

The P300 BCI has a too large response time to be used for issuing a stop command. This section will however describe how it can be adapted to obtain a faster response. An alternative fast BCI based on motor imagery will also be presented.

### A. Stopping With a Fast P300 BCI

While in motion, the most relevant action is to stop the wheelchair. Hence, a menu with only one STOP button can be used when the wheelchair is moving toward its destination. In this configuration, the other buttons are deactivated, i.e., do not trigger a selection even when their score reach the threshold. As a consequence the false activation rate is greatly reduced: when not looking at the interface, buttons scores follow the same distribution, and the probability that their score reaches the threshold is the same for all of them. However, since only the stop button is active, the overall probability of a selection is divided by nine. It is then possible to reduce the threshold, hence the response time, while keeping an acceptable false activation rate.

In our setup, scores are averaged over the last three rounds; the stop button is selected if its score is higher than the eight others and higher than the threshold. In that configuration, the maximum number of false activations per minute is 20. Besides, since only the stop button can trigger a response, thus the error rate does not include selections due to false positives, there is no possible error (i.e., $\mathrm{Err} = 0$) with this interface.

This interface was evaluated using data collected for the evaluation of the P300 interface for destination selection (Section III-A). For each subject, the optimal threshold value was determined so as to minimize the cost function in (1). Normalization factors $[\mathrm{RT}] = 5$ and $[\mathrm{FA}] = 2$ were used as we expect RT to be in the order of 5 s and FA in the order of two occurrences per minute.

### B. Stopping With a $\mu/\beta$ BCI

The alternative fast BCI we have tested relies on motor imagery and is described in [22]. It has been shown that people can learn to regulate the EEG power in the $\mu$ (8–12 Hz) and $\beta$ (18–26 Hz) bands by imagining left or right movements. This ability can be used as a control channel as follows.

EEG is recorded over the sensorimotor cortices (using six electrodes FC3, FC4, C3, C4, CP3, CP4, which are a subset of the electrodes used for the P300 BCI, see Fig. 2). Before a user starts using the system, the baseline $\mu$ and $\beta$ powers for each channel must be computed, which will be used as reference. To obtain the baseline, the user is asked to stay in "idle" state, in which the user does not move or try to regulate his EEG power, during three minutes. The collected baseline EEG signal is then divided into 250 ms segments, and the $\mu$ and $\beta$ powers in each segment are calculated by using the fast Fourier transform (FFT), then averaged to obtain the baselines.

In the control stage, the computer calculates the EEG powers in $\mu$ and $\beta$ bands in each 250 ms EEG and forms a joint feature vector consisting of 12 variables (six channels and two frequency bands): $\vec{x} = \{x_1, \ldots, x_{12}\}$. The control output $y$ is given by $y = \vec{w} \cdot (\vec{x} - \vec{x_0})$, where $\vec{x_0}$ denotes the vector of baseline powers. The vector $\vec{w}$ can be learned using empirical data [23]. Visual feedback in the form of a cursor with position proportional to the value of the control output $y$ is presented to the user.

While most people can use a P300 interface [24] without training, using a motor imagery based interface generally requires lengthy training. Two subjects (A and B) who were able to move the cursor within a couple of seconds after a short training (in the course of a previous study with motor imagery) were selected to participate in our experiment. One of them reported using left and right hand finger tapping to control the cursor, the other imagined himself walking and making left or right turns.

In a first experiment, their response time was evaluated by asking them to move the cursor beyond the threshold line as fast as possible following an audio cue, for 30 times. In a second experiment designed to evaluate the false activation rate, they were instructed to simply relax for five minutes.

### C. Effect of Motion on the Performances

The perception of motion by the brain and the stress induced by sitting on a moving robot are factors that might prevent the usage of our BCIs to issue a stop command. It was shown in [25] that the P300 signal of subjects placed on a Stewart platform is not affected by sinusoidal motions. However the movements of a wheelchair are less predictable and the background is continuously changing. We tested how the two stopping BCIs performed when the wheelchair was in motion, and compared with the performance obtained when the wheelchair did not move. The subjects were using a BCI while sitting on the wheelchair which was moving on a circular guiding path at a constant velocity of 0.5 $\mathrm{ms}^{-1}$. In a first experiment subjects were required to issue a stop command as fast as possible after a cue. In a second experiment we examined the occurrence of false activation FA, i.e., when a STOP command was issued involuntarily. For this purpose, the subjects were required to not activate the STOP command and were observed for 20 runs of 2 min maximum.

### D. Results

The static evaluation of the P300 interface for stopping yielded results presented in the upper part of Table II: on average subjects could issue a stop command in 6.0 s ($\sigma = 3.4$) and the false activation rate was 1.2/min ($\sigma = 0.8$). The lower part of Table II shows the performances of the static evaluation of the $\mu/\beta$ interface: on average subjects could issue a stop command in 4.9 s ($\sigma = 2.2$) and there was no false activation. No significant difference was observed between static and in-motion performances with either the fast P300 or $\mu/\beta$ interface, and the response times with the two different modalities were also similar (see Table II).

TABLE II
STATIC AND IN-MOTION PERFORMANCES FOR THE P300 AND $\mu/\beta$ STOP BCIS

| | | RT (in seconds) | | | FA (in # per minute) | | |
|---|---|---|---|---|---|---|---|
| | | static $\mu \pm \sigma$ | in-motion $\mu \pm \sigma$ | p-value | static $\mu \pm \sigma$ | in-motion $\mu \pm \sigma$ | p-value |
| P300 | subject 1 | 4.3 ± 1.7 | 4.7 ± 1.1 | 0.21 | 1.2 ± 0.9 | 1.4 ± 0.8 | 0.34 |
| | subject 2 | 5.3 ± 2.0 | 5.8 ± 1.9 | 0.27 | 1.5 ± 0.9 | 1.5 ± 0.9 | 0.77 |
| | subject 3 | 7.4 ± 4.3 | 7.0 ± 2.3 | 0.60 | 1.0 ± 0.7 | 1.2 ± 0.7 | 0.13 |
| | subject 4 | 6.1 ± 2.8 | 6.6 ± 2.3 | 0.32 | 1.2 ± 0.7 | 1.5 ± 1.0 | 0.30 |
| | subject 5 | 6.7 ± 4.5 | 5.6 ± 2.4 | 0.19 | 1.3 ± 0.8 | 1.2 ± 0.7 | 0.80 |
| | average | 6.0 ± 3.4 | 5.9 ± 2.2 | 0.93 | 1.2 ± 0.8 | 1.4 ± 0.8 | 0.13 |
| $\mu/\beta$ | subject A | 4.3 ± 2.6 | 4.9 ± 2.7 | 0.33 | 0.0 ± 0.0 | 0.0 ± 0.0 | 1.00 |
| | subject B | 5.4 ± 1.7 | 7.9 ± 2.2 | 0.22 | 0.0 ± 0.0 | 0.0 ± 0.0 | 1.00 |
| | average | 4.9 ± 2.2 | 5.5 ± 3.0 | 0.15 | 0.0 ± 0.0 | 0.0 ± 0.0 | 1.00 |

TABLE III
EVALUATION OF STRATEGIES TO CONTROL A WHEELCHAIR WITH A BCI

| | BCW | | MAIA [8] | Toyota [26] | Iturrate et al. [7] | |
|---|---|---|---|---|---|---|
| | no false stop | some false stops | | | complex envt. | open space |
| number of false stops | 0 | 1.21 | NA | NA | NA | NA |
| nominal time (s) | 100 | 100 | 100 | 17 | 24 | 64 |
| mission time (s) | 112 | 128 | 200 | 22.88 | 571 | 659 |
| mission time ratio | 1.13 | 1.28 | 2 | 1.35 | 25 | 10.3 |
| concentration time (s) | 12.6 | 28.3 | 200 | 22.88 | 447 | 439 |
| concentration time ratio | 0.13 | 0.28 | 2 | 1.35 | 18.6 | 6.8 |
| total cost | 1.26 | 1.56 | 4 | 2.7 | 43.6 | 17.1 |

## V. COMPARISON OF CONTROL EFFICIENCY

This section evaluates the overall performance of our BCW and compares it with the brain controlled wheelchair systems described in the literature. Simulations are performed of the time taken to move between locations, considering the statistics from above results and from [7], [8], and [26]. To concentrate on the BCI control aspects, the performances are compared on obstacle free paths. We use the following metrics.

- The *mission time*, defined as the time from the moment the user initiates the command to reach a destination to the moment this destination has been reached.
- The *concentration time*, defined as the time spent controlling the BCI.

These metrics are normalized by the *nominal time* which is the minimal time required by the wheelchair to reach the destination. The addition of corresponding *mission time ratio* and *concentration time ratio* will then be used as a *measure of control efficiency* expressing the wish to minimize both the time and the concentration required to perform successful movements.

### A. Performance of the BCW

Our BCW is evaluated from simulations based on the selection times and false stop rates presented in Sections III and IV. The task consists in navigating the wheelchair between locations connected by a 50-m-long path. The wheelchair's nominal velocity is 0.5 $\mathrm{ms}^{-1}$, hence the nominal travel time is 100 s. We analyze two scenarios characterized by the option chosen for stopping the wheelchair. Scenario A considers that there is no false stops. This corresponds to either using the $\mu/\beta$ interface ($\mathrm{FA} = 0$), or to disabling the stop feature. Scenario B corresponds to using the P300 stop interface, hence we will have some false stops from time to time.

With our BCW, the mission time is the time to select a destination plus the total travelling time, which is computed as follows. First, a selection time is picked up randomly according to the RT distribution. For scenario A, the mission time is simply this selection time plus the nominal time of 100 s. For scenario B, a false stop rate is selected randomly according to the FA distribution, and the corresponding time to stop $T = 60/\mathrm{FA}$, as well as the distance travelled by the wheelchair in this time $D = VT$, are computed, where $V = 0.5\ \mathrm{ms}^{-1}$. If this distance is greater than 50 m, the wheelchair has reached the destination without stopping. If the distance is smaller than 50 m, the wheelchair has stopped before reaching its destination and has to be restarted, so a selection time is again picked, and the same process is repeated until the total distance reaches 50 m. The concentration time is the mission time minus the nominal time.

Table III shows the value of the two metrics and the performance cost for scenarios A and B over 500 simulation trials. In scenario A, the mission time is 112 s on average ($\sigma = 5$ s), the concentration time ratio is 0.13 and control efficiency is 1.26. In scenario B, the mission time is 128 s ($\sigma = 13$ s) with an average of 1.2 false stops ($\sigma = 0.8$), yielding a concentration time ratio of 0.28 and control efficiency measure of 1.56. It is also worth noting that in the case of scenario A, the 12 s overhead is independent from the length of the path.

### B. Comparison With Other Wheelchair Systems

To put the above results in perspective, we compute the same cost function on results published by other brain controlled wheelchair projects [7], [8], [26]. In the MAIA project [8], average trajectory times range from 130 to 270 s depending on subject and active behaviours. Taking 200 s as their mean mission time yields a mission time ratio of 2. Since the control of the wheelchair requires continuous concentration, we take

200 s as the concentration time, yielding a concentration time ratio of 2 and a control efficiency of 4.

We next evaluate the cost of the Toyota/Riken wheelchair [26]. One subject managed to drive the wheelchair on an eight-shaped course in 22.88 s on average ($\sigma = 0.16$ s). While driving on the same course with a joystick, the average time was 16.96 s ($\sigma = 0.086$ s), hence the mission time ratio is 1.35. Since the control of the wheelchair requires continuous concentration, we take 22.88 s as concentration time, yielding a concentration time ratio of 1.35 and the control efficiency is 2.70. Note that this corresponds to the results of a subject which may be exceptional, and more subjects are required to confirm the performance.

Data for the brain controlled wheelchair by Iturrate *et al.* [7] is also available, which was evaluated on two different circuits. The first circuit was designed to accomplish complex manoeuvrability tasks and avoidance of obstacles in constrained spaces (length of optimal path: 12 m). The second circuit involved navigation in open spaces (length of optimal path: 32 m). The respective mean mission times were 571 and 659 s, and the respective concentration time were 447 and 439 s. From this data, the mission time ratios can be computed as 25 and 10.3, and the concentration time ratios as 18.6 and 6.8, yielding control efficiency measures of 43.6 and 17.1, respectively.

Table III summarizes the evaluated measures for each of those strategy in comparison with our strategy.

## VI. Discussion

Current BCIs enable one to deliver commands only infrequently or with very low confidence. Given that fact, two main questions are 1) whether current BCIs can be used to control a wheelchair safely and efficiently? and 2) which control scheme is more appropriate?

To develop a brain controlled wheelchair for navigation in familiar environments, we decided to use a slow but reliable interface for destination selection, and motion guidance for safe and autonomous navigation. The results obtained with healthy subjects demonstrate that our strategy enables them to move the wheelchair in a building environment safely, efficiently, with limited effort and in a reasonable time. Although we have not tested the BCW with individuals who are locked-in, previous studies have shown that these subjects are able to use the P300 and $\mu/\beta$ BCIs, and that their performances are roughly similar to those of healthy individuals [27]–[30].

With our BCW the user needs about 15 s to select one of nine context dependent destinations with almost 100% confidence using a P300 BCI. Using either a fast P300 BCI or a $\mu/\beta$-BCI the user can stop the wheelchair during motion within 5 s on average. This time corresponds to a distance of 1.5 m at the nominal velocity of 0.5 $\mathrm{ms}^{-1}$. Therefore, an additional sensor-based system is required, implemented in our system using an ultrasonic sensor.

To put these numbers in perspective, we can compare the BCI control with conventional joystick based control: healthy subjects may be able to generate a stop command in about 100 ms, however disabled subjects as tested in [31] will have less than perfect commands such that for example the hand may vibrate widely, and will typically not be able to stop the wheelchair in less than 1 s.

The two BCIs tested for stopping showed both similar response times. The $\mu/\beta$ interface had no false stops, however it requires significant training, thus may not be used with all subjects. Comparison of performance while moving or not further showed that performances of those BCIs are not affected by motion.

By comparing the movement time and concentration time required to move between locations, our control strategy was found to be more efficient than other existing wheelchairs. The published data do not allow comparison of other factors such as comfort and safety, the reaction to obstacles, financial cost of the equipment, and the amount of training required to use the BCI. However, the comparison with other BCI controlled wheelchairs showed that the control strategy we have proposed enables an efficient control with little mental effort. We believe that these are fundamental conditions for brain control wheelchairs to be actually used.

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