Proceedings of the 2007 IEEE 10th International Conference on Rehabilitation Robotics, June 12-15, Noordwijk, The Netherlands

Controlling a wheelchair using a BCI with low information transfer rate

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Abstract— **This paper describes a control hierarchy to drive a wheelchair using an interface with asynchronous and very low information transfer rate signal. Path guiding assistance allows the user to bring his or her wheelchair in a building environment, from one destination to the next destination. The user can stop the wheelchair voluntarily during movement, or through a reflex elicited by sensors. Decisions are simplified by presenting only the possible selections on the GUI, in a context dependent menu. This system is implemented on a conventional wheelchair with a P300 Brain Machine Interface. Tests with healthy subjects show that this system can move the wheelchair in a typical building environment according to the wishes of its user, and that the brain control is not disturbed by the movement.**

I. Introduction

Alternative Input Devices (AID) available on the market can help physically challenged people to control computers, communication devices or a wheelchair. This includes a simple stick held between the teeth, buttons and joysticks of various sizes that can be activated by various parts of the body, gaze tracking systems or head movement based systems to enable control of a cursor on a screen, or even relatively new Brain Computer Interfaces (BCI) for direct control of a computer by thought.

While there exists a great number of AID, in many cases controlling a device still remains a challenge. For instance, a person with poor motor control and large tremor will have problems to actuate even a system with a single switch, as we experienced recently [1]. As a consequence the delay between clicks may amount to several seconds, and it is impossible to produce a command at regular intervals. Further, the button may be pressed involuntarily.

Communication is even more difficult for locked in people such as individuals suffering from Amyotrophic Lateral Sclerosis, a degenerative disease of the motor neuron which, in the advanced stage, leads to complete paralysis of every single muscle in the body. These persons cannot use a conventional AID, but may be able to communicate with other people and devices using a BCI. For instance, an electroencephalograph (EEG) BCI uses the electric signal measured on the scalp to detect voluntary commands. However, the EEG signal is very noisy and has a large variability. Therefore, either the uncertainty on the command will be high, or the time between consecutive commands will be long, in the order of seconds.

Fig. 1. Photograph of the prototype wheelchair controlled by thought, which can move in a building environment.

Can such a poor signal be used to safely and efficiently control a wheelchair that requires a real-time specification of its position within the three dimensional space of planar motion? This is the challenge we address in this paper. We examine how to control a wheelchair using a signal which is *asynchronous* and has an *ultra-low information transfer rate*. We propose a robust control strategy, which we then test on a Brain Controlled Wheelchair (BCW) (Fig. 1). This application is challenging, as, in addition to the multidimensional workspace, the user has to control safety. Safety is even more important for a wheelchair user as for a healthy driver, who is more subject to severe injuries because he or she cannot react appropriately to an accident.

A solution to use an infrequent signal for controlling a wheelchair consists in endowing the system with some autonomy, such that the user only needs to provide simple directives from time to time. A conventional approach toward autonomy is to equip the vehicle with sensors to perform obstacle detection and localization. The robot has to be given sufficient artificial intelligence to generate a suitable trajectory to the destination. However this strategy has a heavy cost (both financial and computational) and the decision taken by the system might seem awkward to a human observer [2]. Hence autonomous vehicles have been observed to refuse to move forward due to some obstacles, while a human driver would easily be able to move its way through [3].

For all these reasons, we decided to develop a motion control strategy based on human supervision rather than on sensor based reasoning. We constrain the movement to guidepaths joining locations of interest in the environment. These paths, defined by the user or a helper, are stored in the computer memory forming a geometric graph of the environment. The wheelchair user can then select a desired destination using a context dependent menu showing him or her the current possibilities, and a path following controller automaticaly drives the wheelchair along the appropriate path.

This paper presents the robust control strategy we propose for vehicles controlled with an asynchronous and low information rate command signal (Section II). It describes the working prototype of the brain controlled wheelchair (BCW) we have developed [4], which uses this control strategy and a P300 BCI, as well as experiments we performed to test this robotic wheelchair in real conditions (Section IV).

BCI have so far been used at static positions [5]–[11], and it is not obvious that they work satisfactorily when the user is moving in the environment. However for our wheelchair we need reactions of the user during movement. We have thus developed an algorithm enabling intervention of the user during movement, which is presented in Section III describing the P300 BCI. We also performed experiments to investigate whether the control is affected by the movement, which are also described in Section IV.

II. Robust and Safe motion control strategy

A. Motion guidance provides driving assistance

In order to adress the contradictory contraints of low information transfer rate signal and the wish of the user to control the wheelchair movement, we need a simple and robust control strategy. We propose to represent the environment by a geometric graph of guiding paths connecting locations of interests. Fig. 2 shows such a map for a typical home environment. This simple map of the environment can be built up automatically if a plan of the building is available. Alternatively, it can be formed using *walk through programming*, i.e. the on-board computer records the trajectory while a helper is pushing the wheelchair between two locations and a least-square fit with a B-splines is used as guiding path for subsequent movements.

Using a guiding path map, navigating with the wheelchair becomes fairly simple. The GUI prompts the user with the

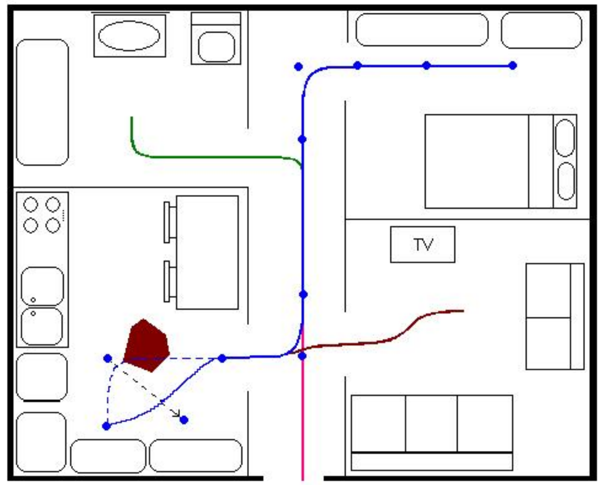

Fig. 2. Example of a map with guiding path in a home environment. The paths are defined by a small number of control points which have a clear geometric meaning as attraction points of a B-splines, and can be used to modify the path. For example the figure shows how the path in the kitchen is modified to avoid a large object which makes obstacle.

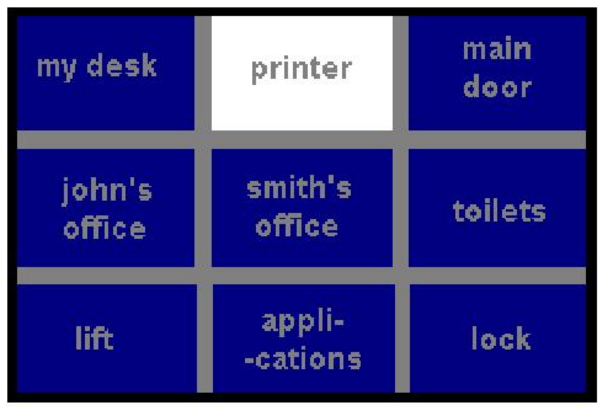

Fig. 3. Context dependent menu for selection of the next move. When the wheelchair reaches a destination, the commands displayed to the subject are updated to the new destination. Note that the number of commands is not limited to nine. In particular, for the P300 BCI the number of possible command displayed on the GUI amounts about 30.

destinations connected to the current location. Therefore the menu presented on the GUI is context dependent, which reduces the selection to a few possibilities and thus reduces the complexity of the selection process. Upon selection of a destination, the path controller [12], [13] moves the wheelchair along the path to its end.

The wheelchair user or a helper can easily modify the guiding paths to adapt to modifications in the environment such as changes in the furniture locations or obstacles. Simple and efficient tools for path editing are described in [14]. It is also very easy to extend the map by adding new paths and nodes, or connecting two maps together, for instance at a lift.

B. Localisation

Using guiding paths, our system does not require to model the environment, thus it does not need complex sensor or sensor processing. However, successfully negotiating a

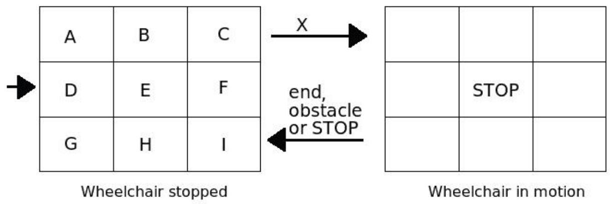

Fig. 4. Control diagram and representation of the interface. This extremely simple control scheme makes navigation very intuitive.

way through a door or a congested environment with our motion guidance strategy requires to know the position of the wheelchair within few centimeters. Localization with such precision is obtained by combining local information provided by the odometry with some global position information using a Kalman filter.

Global position information can be obtained using various technologies: triangulation with respect to some fixed radio or laser emitters, such as with [15], [16]; recognition of some known places in the environment [17]; or proximity to beacons placed at known position. These beacons can be for example black and white patterns fixed to the ceiling, which are detected by cameras pointing to the ceiling [18], or RFID [19], or bar-codes patterns. These technologies come at different costs and precision can range from meters to millimeters.

As will be described in Section IV, our wheelchair prototype is using bar-code patterns disposed on the floor at strategical locations along the paths as beacon. This system provides sufficient accuracy [14] at a very low cost.

C. Control hierarchy

The state of the control is represented in the context dependent GUI, which proposes only current possibilities to the user (Fig. 4). In the first state, the wheelchair is stopped, waiting for an instruction from the user, for instance a destination. The destinations displayed on the GUI (e.g. the 3x3 matrix on the left of Fig. 4) are the destinations which can be reached from the current location.

When a destination is selected, the wheelchair progresses along the corresponding guiding path to this destination, and a GUI with only the STOP possibility is presented to the user. When a destination is reached, the GUI is updated with the possible next destinations. If a STOP is issued during the movement, the wheelchair stops, and the GUI displays only the two possible destinations from this point, i.e. the start and end of this path.

As the voluntary STOP may come too late, simple sensors . These includes typically laser range finder, ultrasonic and similar sensors as well as contact sensors.

At a node, neighboring locations are offered; when stopped in the middle of a path, the only possibilities are the two extremities; at a connection point, the name of other maps are also displayed, for instance at a lift it would the list of levels.

III. Maneuvering a wheelchair by thought in a building environment

The above control structure has been tested by implementing it on a Brain Controlled Wheelchair. The BCI is an extreme case of an interface using an asynchronous and low information rate signal, and this application thus tests the robustness of the control strategy.

Our BCI is based on EEG, which provides a continuous time measurement with a simple portable system. Physically, a set of electrodes fixed on a cap is wired to an amplifying-filtering-digitizing device, which transfers the signals to a computer for analysis.

A. P300 based brain interface for item selection

The *P300 evoked potential* is a well studied and stable brain signal. It is a natural and involuntary response of the brain to rare or infrequent stimuli, which can provide a BCI through an *oddball paradigm*. In this paradigm a random sequence of stimuli is presented, only one of which is of interest to the subject. Around 300 milliseconds after the target is presented, a positive potential peak is recorded in the EEG signal. Upon detection of this P300 signal (P for positive, 300 for the 300 ms delay), the target can be determined as the stimulus that occurred 300 ms earlier.

We are using a visual *oddball paradigm*. Items to be selected are displayed on a screen and flashed one by one in a random order (see Fig. 3). To select one 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. The item on which the subject is focusing his or her attention is selected by the P300 BCI. One does not need to gaze at the target on the screen, but only to concentrate on it: the P300 is a measure of surprise, and not a direct visual signal.

The P300-based BCI has the advantage of requiring no training from the user and only a few minutes to calibrate the parameters of the detection algorithm. This is noteworthy since some BCI techniques require a very long training phase, up to several months in the case of slow cortical potential devices [11].

B. Main features of the BCI

For the BCW we are using the asynchronous P300 system described in [20]. The signals from 15 EEG electrodes recorded on the top of the head are first filtered and cleaned from artifacts. These are then segmented to associate each button with a *sample* corresponding to data between 150 ms and 500 ms after this button flashed. These samples are fed to a support vector machine (SVM) which computes a *score* expressing the likelihood that the sample contains a P300.

After each *epoch*, the period during which all buttons are flashed once, the SVM outputs new scores for all buttons. When one or several scores are higher than a *decision threshold*, the button with the maximum score is designated as the target. To avoid exceptions from affecting this selection we actually consider the average score over the last eight epochs.

Critical factors for the P300 BCI are:

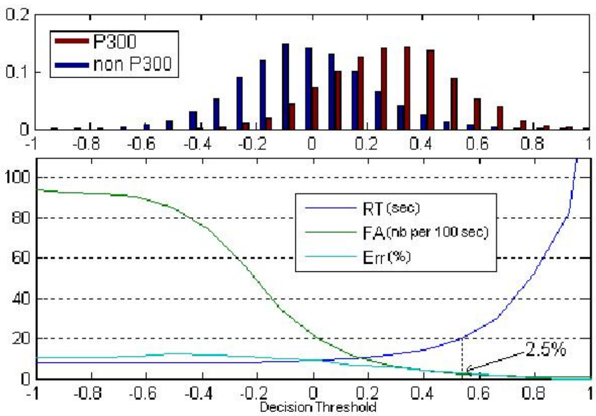

Fig. 5. The top panel shows the distribution of scores of a typical subject for the samples that contain a P300 and those which do not. The lower panel shows how the characteristics of the BCI vary with the threshold. The curves show the mean response time (RT), error rate (Err) and false acceptance rate (FA) averaged over the five subjects. For a response time of 20 seconds, the error and false acceptance rates are as low as 2.5%.

- Error rate (Err): the ratio of wrongly selected targets (substitution) by the total number of selections during an experiment. This error rate is kept low by using the moving average of scores over the last eight epochs to select the target.
- Response time (RT): the time before the (averaged) score of a button reaches the decision threshold.
- False acceptance rate (FA): no button should be selected when the subject does not intend to. The FA is the number of times per hundred seconds that the system wrongly detects a P300 signal though the subject is not trying to give one.

These features depend on the value of the decision threshold. A low threshold leads to a fast selection but may produce lot of errors and high FA. Conversely, a high threshold leads to long RT (possibly no response at all) and low FA.

C. Selection of the decision threshold

To determine a suitable threshold for our application, we measured the response time, false acceptance and error rate as a function of the threshold. EEG was recorded from five young healthy subjects seating in front of a computer monitor. We measured the EEG while they were selecting buttons displayed on the monitor as well as when they were performing other mental tasks such as reading or relaxing. Collected data were processed offline and results are given in Fig. 5

The scores are approximately normally distributed and the P300 scores population is larger than the nonP300 for every subject. The RT curve is bound by a minimum of eight corresponding to the averaging window's width. RT increases with the threshold since there are less samples with a high score. Conversely, FA is close to 100% for threshold values lower than the scores distribution's center, and tends to zero for high values of the threshold. Err is below 10% and decreases for large values of the threshold.

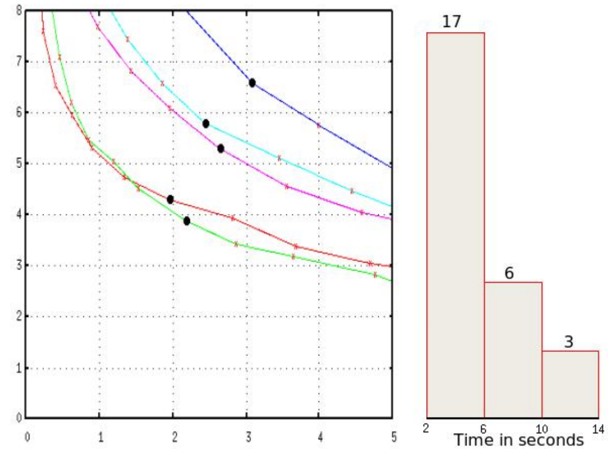

Fig. 6. Left: response time (RT) as a function of the false acceptance rate (FA) for five subjects, offline results. Right: distribution of response times for on-line experiments on the wheelchair (26 trials).

Which value of the threshold to choose depends on the application and desired performances. To control our wheelchair, we choose a relatively high threshold value which yields a low error and false alarm rate. Our results demonstrate that for a value of the threshold that keeps FA around 2.5%, RT will be about 20 s, which is well acceptable. For example, the waiting time in lifts or for a green light on the street is in the order of tens of seconds or minutes.

D. A faster algorithm for stopping

While in movement, the most relevant action is to stop, hence the P300 interface displays only a STOP button. In this configuration we are no longer interested in determining which of the nine buttons the user is selecting, but merely whether the user is trying to select the stop button.

We designed an algorithm providing a faster answer, by concentrating the analysis on this STOP button. After each round, the nine scores are normalized between -1 and 1 with respect to the minimum and maximum value. We consider the mean value of scores over the last N rounds. If the average score of the stop button is the highest and greater than a threshold τ then a stop is issued.

The left panel of Fig. 6 shows the RT as a function of FA for different values of the threshold. These results are obtained by feeding the data recorded in section III-C to the fast P300 algorithm with $N = 5$ and τ ranging from 0 to 6 by steps of 0.25. Crosses mark the threshold points, the black dots mark the points corresponding to a threshold of 3. These results suggest that it is possible to achieve a response time of less than 5 seconds while maintaining the false acceptance rate below 3 occurrences per hundred seconds.

IV. Wheelchair control in real conditions

The P300 BCI is well tested and by now relatively stable for applications like a speller or a TV remote control [20]. However, it is not clear whether it would work on a wheelchair, where conditions are more stressful than at a desk. Similarly, the previous experiments have examined the performance with the BCI when subjects were seating on the front of a computer monitor placed on a table. However, a wheelchair user may be distracted by the environment, the optical flow and the contact with the wheelchair. Can the P300 BCI be used to control a wheelchair, using the control strategy of Section II? To examine this we performed experiments with healthy subjects on a wheelchair prototype, as described in this section.

A. Wheelchair prototype

The Brain Controlled Wheelchair prototype (BCW), described in [14], is built on a Yamaha JW-I power wheelchair. The real-time control program is written in C and runs on a Toshiba M100 laptop with a Pentium 1.2GHz processor operated by Ubuntu linux 6.06 with a 2.6.15 kernel patched with RTAI 3.3 for real-time capabilities. The path following controller is adapted from [12], [13], in which the steering velocity is controlled by feedback linearization of the kinematics.

Sensors are limited to two optical rotary encoders (RI 58-O from Hengstler) attached to specially designed glidewheels for odometry, a bar code scanner for global positioning, and a simple proximity sensor mounted in front of the wheelchair.

The scanner, a Symbol M2004 Cyclone, similar to models used in supermarkets to read price codes, is mounted below the seat. Combined with odometry the system provides sufficiently accurate pose of the wheelchair at a speed up to $0.6m/s$ [14]. This barecode system has the advantage of being cheap and easy to set up: bar-code sets can be printed on a personal printer and disposed.

The proximity sensor, a SRF02 from Devantech, is mounted in front of the wheelchair to avoid frontal collision: if an obstacle is detected within 50 cm, the controller automatically stops the wheelchair.

For EEG acquisition we use NuAmps from Neuroscan, which is a high-quality and inexpensive 40-channel digital EEG system with electrodes and amplifier that is capable of 22 bit sampling at 1000 Hz, measuring signals from DC to 260 Hz. The associated electronic equipment is smaller than a laptop and weighs less than one kilogram.

B. Navigating in a building environment

We conducted various navigation experiment in an our lab building. This environment included several floors connected by a lift. At each floor, four destinations were interrelated by six guiding paths, corresponding to the menus of Fig.3. These guidepaths were designed prior to the experiment using the walk through programming method, i.e. by tracing the paths with the wheelchair and coding the resulting data using B-splines.

We assumed a smart environment with the lift bringing the wheelchair automatically from one floor to the other when the BCI command asks for another floor (see Fig.3 bottom panel). However, the installation of such system is beyond the focus of the BCW, so the lift as well as the entrance and exit of the wheelchair were here operated manually.

Five subjects were asked to move between ten pairs of locations placed on different floors. All subjects succeeded at their first trial to reach each of the desired locations, taking in mean fifteen seconds to issue a command. No wrong command was selected. The subjects reported that it was "very easy" to activate the commands for selecting destinations and change the floor.

C. Reaction during movement

The perception of motion by the brain and the stress induced by seating on a moving robot are factors that might interfere with the P300 BCI and so prevent the usage of our BCI to issue a stop command. More generally, we do not know of any study proving that EEG patterns would remain sufficiently similar during motion as at static position, such that the same control can be used in the two conditions. To investigate this we conducted experiments with two healthy subjects seating on the wheelchair and moving on a circular guiding path.

In a first experiment the wheelchair was launched and the subject was required to issue a stop command as fast as possible. The subjects managed to stop the wheelchair in all trials. The *reaction time* RT was maximally 13 seconds and in about 2/3 of the trials (17/26= 65% of the trials) below 6 seconds, with a distribution shown on the right panel of Fig. 6.

A second experiment examined the occurrence of false acceptance, i.e. when a STOP command was issued involuntarily. In this purpose, the subjects were required to not activate the STOP command and were observed during 2 minutes. Over the 12 trials, no STOP command was issued at all during the 2 minutes in 2/3 of the trials, and a command was issued after 53, 47, 23 and 34 seconds respectively.

These results are conform or better than expected from the off-line results reported on the left panel of Fig. 6. This indicates that the P300 pattern was not significantly modified by the motion.

Altogether, the results of this section suggest that the very low information rate signal of the BCI can be used to move in a building environment. Further the control strategy of Section II is sufficiently robust to move safely in such environment.

V. Discussion

This papers presented a simple robotic system to helps severely disabled people, which can communicate only via a low information rate interfaces, to recover some mobility. A path following controller constrains the wheelchair's motion on safe predefined guiding paths, thus limiting the driving task to the selection of a destination.

During the movement to this destination, the user can stop the wheelchair at wish using a novel faster P300 algorithm which was introduced in the paper. For safety, simple sensors are added to prevent the wheelchair from hitting obstacles on the path. This redundant feedback structure provides safety despite the asynchronous and low-information rate signal, and does not prevent movement, as the user has the overall control.

This control strategy can be implemented with various AID and in fact many AID are characterized by an asynchronous and low information rate signal. An extreme case was tested in the form of a P300 signal from an EEG BCI used to control a prototype wheelchair, which we have implemented. Our experiments showed that, using this P300 signal, subjects are able to move safely in a building environment. In turn, they suggested that the P300 signal is not significantly modified while moving in this environment with the wheelchair.

The system requires a minimum of input and concentration, thus reducing effort from the user. This is critical as for some disabled the effort to use a BCI for communicating is considerable. Moreover, since the movements along the same guiding paths are repeated over time, the predictable wheelchair's motion will contribute to relaxing the user during the movement. This system is easy to use, and also simple to set up since no major modification is required in the user's own wheelchair or in the environment, and a map of guiding paths can be designed using simple tools.

While these results are promising, experiments with 'real end users', e.g. locked-in individuals, are critical to ensure that they would also be able to use our wheelchair system satisfactorily.

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