A Brain-Controlled Wheelchair Based on P300 and Path Guidance

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***Abstract*— This paper presents the first working prototype of a brain controlled wheelchair able to navigate inside a typical office or hospital environment. This Brain Controlled Wheelchair (BCW) is based on a slow but safe P300 interface. To circumvent the problem caused by the low information rate of the EEG signal, we propose a motion guidance strategy providing safe and efficient control without complex sensors or sensor processing. Experiments demonstrated that healthy subjects could safely control the wheelchair in an office like environment, without any training.**

***Index Terms*— wheelchair; BCI; P300; path following**

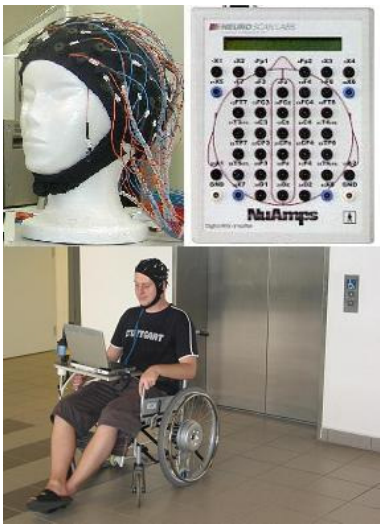

Fig. 1. Photographs of the acquisition devices and brain controlled wheelchair during experiments in a typical office environment. Note the compact portable system including signal amplifier, filter and acquisition device.

I. Introduction

Controlling objects or machines by thought is a dream which is currently moving from science fiction to science and technology. This paper introduces the first working prototype of a Brain-Controlled Wheelchair (BCW) able to maneuver in a typical office or flat building, designed for people who are not able to use other interfaces such as a hand joystick or gaze tracking, and in particular for patients suffering from Amyotrophic Lateral Sclerosis (ALS)[1]. Our goal is to develop a system usable in hospitals and homes with minimal infrastructure modifications in order to help these people regain some autonomy. Such a system has to be *safe* and easily set up at a relatively low-cost.

Development of brain machine interface (BMI) or brain computer interface (BCI) has flourished in past years. It has been recently demonstrated that neural implants placed in the brain of animals or humans could be interfaced to move simple mechanisms [1]–[4]. Since such invasive techniques are still risky, research in *human BCI* mainly focused on non-invasive methods for monitoring brain activity, such as electroencephalography (EEG), magnetoencephalography (MEG), near-infrared reflectance spectroscopy (NIRS) and functional magnetic resonance imaging (fMRI).

EEG is the most common recording method used in BCI, providing a continuous time measurement with a simple portable system. In EEG, a set of electrodes are applied on the scalp and wired to an amplifying-filtering-digitalizing device, which transfers the signal to a computer for further analysis specific to the paradigm and application. The electronic equipment needed is currently smaller than a laptop and less than one kilogram. Various techniques have been developed in the last years to enable the utilization of an EEG as a communication mean between a human and a machine [5].

Section II gives an overview of the different techniques based on EEG that have been developed to read the mind, in particular the P300 technique we are using for our wheelchair. As it will be seen, the main problem is that the signal is noisy and the information transfer rate is low, thus a-priori not well compatible with the continuous control of a machine[2]. A solution to achieve brain

[1]ALS is a degenerative disease of the motor neuron which, in the latest stage, leads to complete paralysis of every single muscle in the body. More information about ALS can be found online at http://www.alsa.org.

[2]Published results suggest that invasive techniques using neural implants have to deal with similar problems at present.

control of a machine may be to endow the machine with some autonomy, such that the user only needs to provide directives from time to time. The last twenty years have seen the development of autonomous robots equipped with sensors, which can move in complex environments. Such autonomous robot systems may be used for a wheelchair.

Hence Del Millan et al. [6] utilized a neural network classifier for recognizing mental states in a eight-channels EEG in order to achieve real-time control of a mobile robot. These mental states determine the commands to a Khepera robot. A mental state is the brain wave pattern produced while performing a specific task such as relaxing, imagining movements of the left or right hand, performing cube rotations, arithmetical operations or word associations. The main assumption is that these mental states do not change over time and remain associated with these tasks. After two hours of training per (healthy) subject, the classifier is able to discriminate three mental states within 0.5 seconds with an accuracy of 70%. Similarly, Tanaka et al. [7] recently used thirteen-channels EEG with right and left states to decide upon the next move of a wheelchair. However the number of repetitions necessary to complete even a simple movement may exhaust the subject. In particular we experienced that disabled get easily tired.

In [6], subjects use mental states to control the trajectory of a Khepera robot in a small office-like environment (see figure 2a) by relying on the robot's sensors and autonomous behaviors. To cope with classification errors, the Khepera is equipped with autonomous behaviors such as corridor following and obstacle avoidance hence providing time for the user to focus and quickly correct his or her mental state. However this will still require him or her to be constantly alert, and hence may cause stress. Furthermore, the motion depends on the sensors and complex sensor-processing with which the robot must be equipped, and these are costly and not foolproof. Therefore, this type of control may be too risky for a wheelchair on which the user is seated.

The strategy we propose to control a wheelchair relies on a slow but safe and accurate brain interface. We use a P300 based BCI which is characterized by typical error rates of 3% [8] with a response time up to several seconds. In order to simplify motion control, the wheelchair is constrained to move along paths predefined in software joining registered locations (see section III-A). The guiding paths can be entered into the system using a simple and efficient path editor presented in section III-B, which also enable helpers to adapt it to changing environmental conditions. The user's task then only consists of selecting the destination and dealing with unexpected situations through a dialog scheme that is described in section III-C. Thus the system requires a minimum of input and concentration from the user. Section IV reports the experiments performed in order to adapt the P300 for this particular application and to test the overall system.

II. P300 BASED BRAIN INTERFACE

Various signals can be extracted from the EEG to develop BCIs [5], including the slow cortical potential [9],

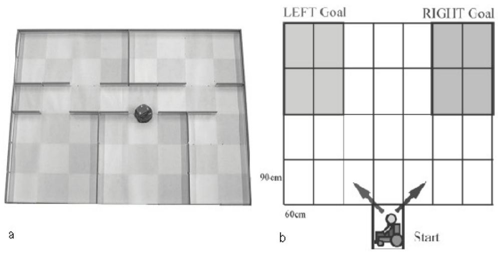

Fig. 2. Related previous systems. a) With the system of [6] the user can control a Khepera robot through a small office like environment by issuing high-level commands such as turn right at next occasion or follow left wall. b) The system of [7] detects left and right intentions of the user to decide upon the next move of the wheelchair.

μ and β rhythms [10], motor imagery [11], P300 evoked potential [12], and static-state visually evoked potentials [13].

P300 potential is a well studied and stable potential difference at the central or parietal sites of EEG measurements corresponding to rare or infrequent events. A set of items are displayed on a screen and flashed one by one in a random order, with only one of them – the target – being relevant for the subject. The subject is instructed to focus his or her attention on the target. One simple way for focussing is, for example, to count the number of times the target is flashed. The subject does not need to gaze at this object, but only to concentrate on it. The P300 is a measure of surprise, and not a direct visual signal. A positive potential typically occurs around 300 milliseconds after a rare event, from which the target can be determined. After several presentations of the items the target can be recognized with almost 100% confidence.

This setup has the advantage of requiring no training from the user and only a few minutes to train the P300 detecting system. This is noteworthy since most of the other BCI techniques require a very long training phase, up to several months in the case of slow cortical potential devices [9].

In our prototype of the Brain-Controlled Wheelchair, we used the single display paradigm P300 system (SD-P300) [8] developed by the A*STAR Institute for Infocomm Research, Singapore. The system has the following characteristics:

- Use of 15 EEG channels.
- Noise and artefact suppression using principal component analysis.
- P300 detection with a Support Vector Machine (SVM) algorithm.
- Statistical model for P300 verification and non-target signal rejection [14]: the SVM margin score is converted into a probability and the ratio of probabilities of signal containing/non containing a P300 is compared to a threshold.

Setting the threshold has a direct influence on the accuracy and latency of the system: with a low threshold the system is fast but may commit classification errors, which might be a desirable setting for a speller. On the other hand, if the threshold is high, the system will make very few errors but the response time will be long. To control our wheelchair we need a very safe BCI thus we set the threshold to a high value, even if it results in a long response time. Section IV-A reports evaluation of the SD-P300.

III. Safe and Simple Control

To cope with the low information transfer rate of the P300 based BCI we need to provide sufficient autonomy to the robot. It must be able to navigate safely in its environment and deal with basic situations. The user input should limit to destination selection.

A conventional approach to autonomous mobile robotics would be to equip the vehicle with sensors and sensor processing as necessary to perform localization and obstacle detection, and to give the robot sufficient cognitive ability to react appropriately: i.e. generate a suitable trajectory that will achieve the objective of the mission (eventually reach a goal) while insuring safety. However this has a heavy cost (both financially and computationally) and the decision taken by the system might seem awkward to a human observer. For instance autonomous wheelchairs have been observed to refuse to move forward due to some obstacles [15], while a living organism would easily move its way through. This type of behavior is highly undesirable for a robot conceived to transport persons, as the users, generally equipped with superior sensory and inference abilities to the artificial system, will become frustrated. At this stage, because autonomous vehicles often lack sufficient cognitive abilities, their designer, for safety sake, usually make them over cautious, which often lead to dead-lock situations in uncontrolled environments.

A. Path Guidance Strategy

In our approach, we propose to rely on the user's perception and cognition as much as possible in order to solve the maneuvering problem. The user makes the motion decisions, while the vehicle is in charge of realizing these decisions. With such an approach, the robot is no longer trying to replace the human user but to *collaborate* with him or her, such that both the human and its robot are used to the best of their respective abilities to produce safe and efficient motion.

We simplify motion control by using a set of safe pre-defined guiding paths between the different relevant locations. When a path is selected, the robot drives it along the path using a dedicated path controller based on the controller in [16], [17]. This circumvents the need for complex sensor processing and for dynamic trajectory computation that is otherwise required to reach the destination without hitting obstacles.

An important issue when using software-defined paths is localization: the position of the wheelchair must be known with a precision in the order of a few centimeters. To keep the system simple and cost-effective, the wheelchair is equipped with a simple global localization module [18] using fusion of local information from odometry and global position information from a simple bar-code reader. A set of bar-codes are placed on the floor at key positions such as near doors or narrow corridors. When the vehicle passes over a bar code, global position is provided to the system to update the position. This system has proven to be simple to set up and sufficiently accurate for our purposes. The maximum positioning error is always less than 10cm when bar codes are placed about every 10m.

A library of guiding paths can be built up automatically if a reliable plan of the building is available. Alternatively such a library can be formed by a helper pushing the wheelchair to link various rooms as is necessary for the wheelchair user. As described in the next section, the helper has various ways to adapt the paths to permanent modifications in the environment such as changes in the furniture locations. Also, paths corresponding to a building, an office or an apartment can easily be extended to include paths leading to further space such as a neighboring office.

B. Ergonomic Guiding Paths Editor

The path editor contains several tools which enable a helper to design guiding paths suitable to the environment and satisfying the wishes of the wheelchair user [19]. The first tool is the *Walk Through Programming* or WTP, which works as follows: the helper pushes the wheelchair through the environment along a suitable trajectory. While driving along this path, the wheelchair is automatically recording the sequence of positions. The traced path is then least-squares approximated with cubic B-splines, and used as a guiding path for subsequent motions. If the wheelchair user is not satisfied with this path, the helper can use a dedicated graphical user interface (GUI), the second tool, to modify it off-line (Fig. 3), or retrace it altogether.

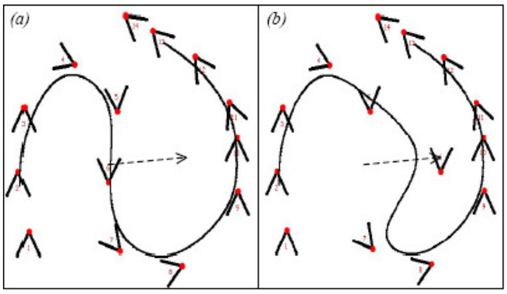

Fig. 3. (a) Off-line modification of a guiding path by moving a control point with a mouse and (b) the resultant modified path.

One major advantage of these design tools is their great simplicity. They require no environment model and no complex operator procedures. When building a network of paths it is possible to reduce the amount of WTP tracing by concatenating chunks of paths using our GUI. These tools also enable the helper to modify a path for a modified environment (e.g. if there is a new obstacle) or to optimize a path as desired by the wheelchair user.

C. Selection of context dependents paths

The only task for the user is to select a path among a list of paths that depart from the current location proposed on the GUI (figure 4). Once a path is selected the movement is performed automatically until the end of the path is reached, and the user is asked again where to go. The menu shown on the GUI is context dependent, i.e. only possible destinations from the current position are presented.

Fig. 4. The brain wheelchair commands displayed to the subject. These items are flashed (i.e. *office* and *level 7*) in a random sequence on the screen, the user is focusing his or her attention on one of them, and a particular signal is produced about 300*ms* after this target command was flashed, which is detected by the program. The number of commands is not limited to nine and commands are context dependent. For example, the top menu corresponds to the wheelchair navigating at one floor, the bottom menu to the lift situation (wheelchair is currently at level 5 thus it is not displayed).

Typical context dependent menus include all the rooms available on the current floor, and the lift. When the wheelchair is at the lift, the GUI shows the list of levels. When a level is selected, the lift is controlling the wheelchair in the lift, bringing it at the selected level and also controlling its exit. We assume a smart lift able to communicate wirelessly with the wheelchair computer, and equipped with sensors to control the wheelchair.

Note that in contrast to EEG interfaces such as used in [6], [7], in which only two or three mental states can be selected from, with our interface it is possible to select between twenty or more buttons. Therefore, choosing between ten levels at a lift can be done in one step with a P300 (while it would require three or more successive decisions with the systems of [6], [7]) and thus seems particularly adapted to motion planning in an office-like building or in a hospital.

Our P300 BCI is very reliable to choose a destination and start the wheelchair. However, since it has a response time up to several seconds, it is not suitable to stop the wheelchair in emergency. To circumvent this problem we will add simple sensors in front of the wheelchair, which will detect any obstacle in the vicinities and immediately stop the wheelchair. Once stopped, the user will be asked what action to perform: resume movement along the guide after the obstacle has disappeared (passing by obstacle), avoid it using the elastic mode [18] by the left or right side or call for assistance. Because of the variety of possible situations (some of them being represented on figure 5), we choose to rely on the user's cognitive abilities rather than to let the artificial system compute a solution based on its generally poorer sensory function.

Fig. 5. Typical situations while encountering an obstacle on the way. On the situation sketched on the left, it is possible to deviate from the path on both left and right sides while on the situation depicted in the middle scheme only the left side is possible because of the wall on the right side. In the case depicted on the right it is not possible to avoid the obstacle, the user would then have the choice to go back to take another route, change the destination or call for assistance. The system relies on the user to take a decision, thus avoiding any mistake of the system.

IV. Experiments and Results

A. SD-P300 evaluation

While the P300 BCI has been tested when used with a spelling system [8], the task of controlling a wheelchair has distinct features. This BCI may fail in controlling the BCW or require adaptation. In particular, when spelling the subject is normally focussing on only this task, while he or she may think to other tasks when controlling the wheelchair. Therefore we first analyzed the performance of the SD-P300 in terms of response time and accuracy with five young healthy subjects focusing on selecting buttons or performing other mental tasks.

In these experiments the interface displayed nine buttons. At each epoch all buttons were flashed with a duration of 100*ms* each, in a random sequence. We collected three sets of data:

The first set was used to train the classifier. The subject was instructed to count the number of time a given button was flashed (i.e. 8 times). Half of the set was used to train the SVM to detect a P300 signal, the other half is used for the evaluation of statistical parameters [14].

The second set was used to evaluate the response time for different values of the threshold. The method for data collection was the same as for the first set but with 50 epochs. For each target we measured the time required for the score to reach the threshold. Figure 6 shows the average response time curve.

The third set was used to evaluate the false acceptance rate: while the system makes no mistake when the user is trying to select a button, it is sometime wrongly selecting a button by itself while the user does not intend to do so. We experienced that this happened in particular when the user is relaxing or concentrating heavily, thus may be due to interference of α-waves (8-12Hz) and β-waves (18-24Hz) with the pattern the SVM was trained to recognize. To prevent this to affect the performance of the BCW, we decided to tune the threshold in order to increase specificity. We collected 50 epochs data as in the second set, with the subject not looking at the screen and performing one of the following tasks: multiplying two numbers of four digits (heavy mental task), reading (light mental task) and relaxing with eyes closed.

The lower panel of figure 6 shows the resulting false acceptance rate curves averaged over the five subjects. From the results of figure 6 it can be seen that for a value of the threshold that keeps the false acceptance rate low the response time is acceptable.

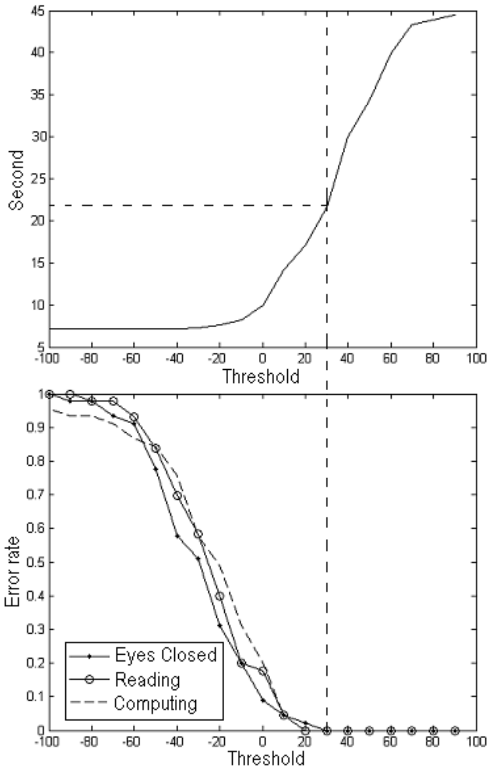

Fig. 6. Characteristics of the P300 when other tasks are performed in parallel to the selection. The curves corresponds to data averaged over five subjects. Top panels: the response time increases rapidly with the selection threshold. Bottom panel: However the false acceptance rate decreases quicker. Therefore it is possible to select a threshold preventing most false acceptance with acceptable response time.

B. Tests in an Office Environment

The BCW was tested in an office environment with five young healthy subjects. This environment included several floors connected by a lift but only two floors were used for the experiments. At one floor, four destinations were interconnected by six guiding paths (Fig.7). The other floor also contains four destinations and six paths. The paths were designed prior to the experiment using the walk through programming method as explained in section III-B.

Subjects were asked to move from one location to another, eventually on the other floor. The lift was manually operated as well as the entrance and exit. Subjects reported that they found it very easy to activate the commands. All subjects succeeded at their first trial to reach the desired locations as they wished, taking approximately ten seconds to issue a command.

Fig. 7. Testing environment: a lift hall, and the six guiding paths between the four destinations.

V. Conclusion

This paper presented the first working prototype of a brain controlled wheelchair able to move in flats or office-like environment or in a hospital. It relies on a path following strategy that provides simple control of necessary movements while avoiding costly and potentially unsafe complex sensor processing, and on a slow but safe Brain Computer Interface used to generate simple commands. The performed tests showed that this system is easy to use and also easy to set up since only a few modifications of the environment are required (placement of a few bar codes). The system also provides tools for users to optimize the guiding paths to the their satisfaction and to adapt to changes in the environment. Finally, because the movements along the same guiding paths are repeated other time, the wheelchair's motion is predictable, so that the user can relax during the movement.

Our current BCI may appear to suffer from the slow response time, however one must replace this in the context of potential users. The system is intended for people who are unable to move and normally stuck in bed; their notion of time is different from ours and being able to move independently within their environment represents a big improvement for their quality of life, whether it takes time or not. In this context, safety and reliability are much more important than speed.

One concern with the slow response time of our BCI, however, is that it prevents fast reaction to any unexpected event such as an obstacle suddenly appearing on the path. As mentioned in section III-C, we are currently working to add simple sensors to stop in front of any obstacle. The motion control simplification brought by the guiding paths enables the use of simple sensors and stop reflexes, which are reliable and safe.

Faster BCI that are expected to appear in the near future will also profit from the significant simplification brought by path guidance and the path editor described in this paper. This will significantly contribute to safety and simplify control without the need of complex sensory processing.

We would like to emphasize that one main next step is to conduct experiments with disabled who really need our brain controlled wheelchair. It is well known that there are significant differences in responses between healthy and disabled individuals, and our future work will depend on experiments with the real end users.

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