Brain Control of a Smart Wheelchair[1]

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Abstract. This paper makes a contribution to the field of autonomous vehicles, especially for use on assistive wheelchairs. The aim of our work consists in the development of a low-cost autonomous wheelchair able to avoid obstacles, self-localize and explore closed environments in a safe way. In order to meet disabled people's requirements, we have designed our system in such a way that it can be simply modified and adapted to the users' needs. In particular, the user has the opportunity to choose among several autonomy levels and three different interfaces: a joystick, a touch-screen and a brain-computer interface (BCI). A BCI is a system that allows users to convey their intention by analyzing their brain signals.

Keywords. Assistive robotics, Interfaces, Localization.

Introduction

The possibility of moving in an autonomous way gives individuals a remarkable physical and psychological sense of well-being. Robotic wheelchairs are usually driven by a joystick and are addressed to those people that are not able to apply the necessary force to move a manual wheelchair. They often are people with low vision, visual field reduction, spasticity, tremors, or cognitive deficits. In order to give these people a higher degree of autonomy, and also to lighten the duties of those who assist them, a large number of solutions have been studied by researchers since the 1980s, by using technologies originally developed for mobile robots to create the so called "smart wheelchairs".

A smart wheelchair, or autonomous wheelchair, typically consists of either a standard powered wheelchair to which a computer and a collection of sensors has been added or a mobile robot base to which a seat has been attached. One of the first examples of autonomous wheelchairs was proposed by Madarasz et al. [1], who equipped a wheelchair with sonars and a vision system to identify landmarks and correct its trajectory in hallways. Another solution was by Levine et al. [2] with NavChair, an electric wheelchair provided with an obstacle avoidance algorithm and multiple task-behaviors to control the movements through doorways or to avoid collision with walls. A more sophisticated solution was Rolland III, proposed by Mandel et al. [3]: a semi-autonomous wheelchair, equipped with laser range finders, encoders and a camera, that is able to set the appropriate speed in the presence of obstacles and avoid them. Following the same topic, Monte-

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sano et al. [4] presented an autonomous wheelchair for cognitive-disabled children, more robust in complex navigation situations such as narrow doors, and populated or cluttered scenarios.

The project LURCH (*Let Unleashed Robots Crawl the House*) fits in with this perspective: the aim of our work consists in the development of a affordable autonomous wheelchair able to avoid obstacles, self-localize and explore closed environments in a safe way. The wheelchair has been equipped with two embedded PCs (about 500 €), a video camera (less than 100 €), an inertial measurement unit (about 2500 €, not used in indoor environments) and two Hokuyo laser range finders (about 1500 €, used only for obstacle avoidance and replaceable with sonars); this equipment provides a self-localization capability and a safe navigation ability to the wheelchair. The smart wheelchair navigates, deals with all the low-level details, avoids obstacles and reacts to emergency situations, while the user decides where (and when) to go in a high-level fashion (e.g., "go to the kitchen"). In order to meet the variable requirements of disabled people, we have designed our system in such a way that it can be simply modified and adapted to users' needs. In particular, the user has the opportunity to choose among several autonomy levels and three different interfaces: a joystick, a touch-screen and a brain-computer interface.

The typical control system used by smart wheelchairs, based on the use of a joystick, is not suitable for totally paralyzed persons. Millions of people in the world suffer from several diseases (e.g., amyotrophic lateral sclerosis — ALS, multiple sclerosis, cerebral paralysis, spinal cord injury) that destroy the neuromuscular channels used by the brain to communicate and control body movements. This calls for the development of a flexible system, able to adapt also to the necessity of completely locked-in individuals. So challenging an objective can be achieved by a system able to determine user's intentions through the analysis of his/her cerebral signals and to transmit this information to an external device, such as a wheelchair. This system is called *brain-computer interface (BCI)* [5]. In general, a BCI is composed of a device that acquires the user's brain signals (e.g., through an electroencephalograph), and a computer that analyzes some predefined components of the signals and maps them into a particular command to be executed. There are several methods to acquire the cerebral signals; among them, we chose to consider the electroencephalogram (EEG) because of the advantages that it brings in terms of non invasivity, practicality, safety and low cost.

1. Wheelchair Design

The smart wheelchairs described in this paper has been designed to provide navigation assistance in a number of different ways, such as assuring collision-free travel, aiding in the performance of specific tasks (e.g., passing through doorways), and autonomously transporting the user between locations. Our aim is to reduce as much as possible the cost of the whole system (the total cost of the framework proposed for indoor environment, wheelchair not included, is less then five thousands of euros, which is cheap with respect to other works) and provide different kinds of interfaces (e.g., the BCI, see the next section for more details), in order to fulfill the needs of people with different disabilities, and to allow users to set the desired level of autonomy.

The LURCH system was designed to be easily adaptable to different kinds of electric wheelchairs. Figure 1 outlines a scheme of LURCH. As it is possible to notice from

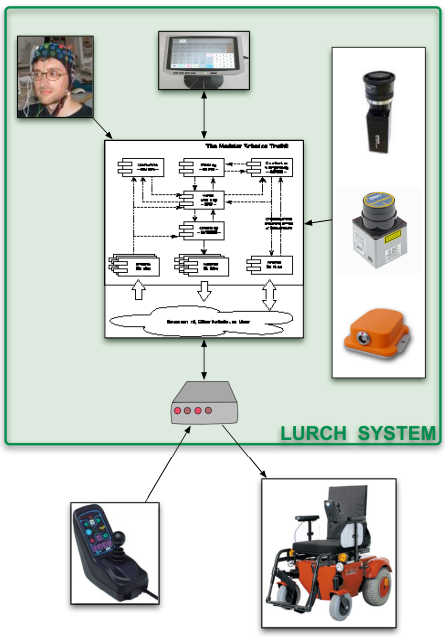

Figure 1. General scheme of LURCH system.

the image, our system is completely separated from the wheelchair, and the only gateway between LURCH and the vehicle is represented by an electronic board that intercepts the analog signals coming from the joystick potentiometers and generates new analog signals to simulate a real joystick and drive the joystick electronics. In other words, we do not integrate our system with the wheelchair at the digital control bus level, but instead we rely on the simulation of the signals from the joystick in the analogue domain. Though this choice could seem awkward, its motivations are twofold: first of all, it is often hard to obtain the proprietary communication protocols of the wheelchair controllers, or to understand how they exchange data with the motors and interfaces; second, this solution improves the portability, since it avoids a direct interaction with the internal communication bus of the wheelchair.

LURCH was designed by adopting a modular approach (as proposed in [6]):

- *localization module*: it estimates the robot pose with respect to a global reference frame from sensor data, using a map of the environment;
- *planning module*: using knowledge about the environment and the robot, this module selects the most appropriate actions to reach the given goals, while respecting task constraints;
- *controlling module*: it contains all the primitive actions, typically implemented as reactive behaviors that can be executed by the robot.

The localization algorithm operates using a video camera and some fiducial markers. These are placed on the ceiling of the environment, since this allows to avoid occlusions, and provide an accurate and robust pose estimation. Of course, this restricts the

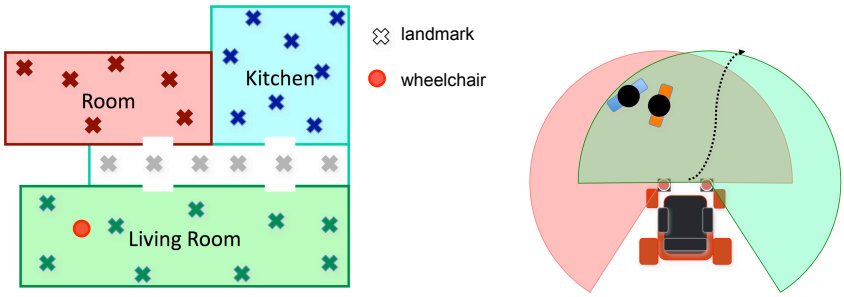

Figure 2. Example of localization and obstacle avoidance.

use of LURCH to indoor environments. Usually, a fiducial marker is a planar patch with a known shape that contains some encoded information. In this work we decided to use the ARToolKitPlus [7] system, where the markers are squares with a black border, and the information is encoded in a black and white image represented in the square. The marker identification process is defined by three steps: identification of possible markers in the image captured by the camera, rectification of the image, and comparison of the information represented in the markers with the database of known landmarks. If a marker is recognized, with the knowledge of its dimension, it is possible to estimate its 6 DoF position and orientation in the camera reference. Since the position and the orientation of the markers in the environment w.r.t. the absolute frame and also the position and the orientation of the camera w.r.t. the wheelchair are known, the system can estimate the pose of the wheelchair w.r.t. the world frame every time it is able to detect a marker. In fact, when a marker is detected, it is possible to estimate the matrix T_M^C that represents the rototranslation of the marker w.r.t. the camera frame. The position of the camera w.r.t. the marker can be easily estimated by calculating $T_C^M = (T_M^C)^{-1}$. Thus, by knowing the spatial relationship between the markers and the world, the position of the camera w.r.t. the absolute frame can be determined. In indoor environments, it is generally sufficient to know the 3 DoF pose of the wheelchair; thus, we decided to simplify the problem, improving in this way the robustness and the accuracy of the localization algorithm.

The trajectory planning is obtained by SPIKE (Spike Plans In Known Environments), a fast planner based on a geometrical representation of static and dynamic objects in an environment modeled as a 2D space (see [6] for more details). The wheelchair is considered as a point with no orientation, and static obstacles are described by using basic geometric primitives such as points, segments and circles. SPIKE exploits a multi-resolution grid over the environment representation to build a proper path, using an adapted A^* algorithm, from a starting position to the requested goal; this path is finally represented as a polyline that does not intersect obstacles. Moving objects in the environment can be easily introduced in the SPIKE representation of the environment as soon as they are detected, and they can be considered while planning. Finally, doors or small (w.r.t. the grid resolution) passages can be managed by the specification of links in the static description of the environment.

Our control module is MrBRIAN (Multilevel Ruling BRIAN) [8], a fuzzy behavior management system, where behaviors are implemented as a set of fuzzy rules whose antecedents match context predicates, and consequents define actions to be executed;

behavioral modules are activated according to the conditions defined for each of them as fuzzy predicates, and actions are proposed with a weight depending on the degree of matching (see [8] for more details).

2. Brain-Wheelchair Interface

There are several kinds of brain activities that can be used in a BCI. Some BCIs register the involuntary brain activity in response to stimuli associated with possible commands in order to infer the command intended by the user. Others analyze components of brain signals that can be controlled voluntary by the user; these BCIs may feel somewhat more natural to the user, as they do not need external stimulation, but users need some training.

In this study, we focus on the first approach; in order to detect user's commands, we used the event-related potential *P300*, while in order to detect and verify user's and autonomous control errors, we considered the *error potential* (ErrP).

2.1. The P300 Potential

The P300 is an event-related potential (ERP) which can be recorded via EEG as a positive deflection in voltage at a latency of roughly 300 ms in the EEG after a defined stimulus. It follows unexpected, rare, or particularly informative stimuli, and it is usually stronger in the parietal area. Stimuli can be visual, auditory, or even tactile.

A P300-based BCI presents the user with some choices, one at a time; when it detects a P300 potential, it selects the associated choice. The user is normally asked to count the number of times the choice of interest is presented, so as to remain concentrated on the task. As the P300 is an innate response, it does not require training on part of the user. Detecting a P300 in a single trial is very difficult; therefore, repeated stimuli are normally used to select the stimulus most likely to have generated a P300. The number of repetitions can be predetermined for each user to get the best trade-off between speed and accuracy.

Many techniques for detecting the P300 extract relevant features from the EEG signal and feed those features into a classifier. In these approaches, feature extraction becomes the key point, and doing it by hand can be at the same time cumbersome and sub-optimal. We have faced the issue of feature extraction by using a genetic algorithm able to retrieve the relevant aspects of the signal to be classified in an automatic fashion.

A P300-based BCI makes possible to build a very flexible system, which allows both communication and the control of different devices with a single graphical user interface. Such an interface renders all the possible choices in a menu on a screen, and highlights them one at a time. Different menus can be built for different tasks or environment, and menus can also be linked to each other. The use of P300 in the LURCH project makes the system versatile, as it is composed by context-sensitive menus that can have as many choices as they are needed, while the selection interface can be kept uniform.

2.2. The Error Potential

Real BCIs sometimes misclassify user intent, and much research is devoted to improving BCI classification ability in order to increase their performance. Another way to face the issue is, as previously mentioned, to repeat the process more than once until a sufficient

Figure 3. Menu for the selection of a room as destination

confidence is reached. Another possibility is, finally, to ask directly the user to confirm his/her choice, by adding another interactive interface.

In this work we adopted an alternative way to improve BCI performance, i.e., the early identification of errors and their automatic correction. It is known from the literature that user's and BCI errors elicit error potentials (ErrP), a particular kind of potentials that occurs in the EEG when a subject makes a mistake or, more relevant to BCI applications, when the machine the subject is interacting with does not behave as the user expects. Thus, the detection of ErrPs could be a viable way to improve BCI performance and to increase its reliability, without making the interaction with the user heavier.

3. Experimental Results

The LURCH data-acquisition and processing subsystem consists of two on-board computers (one to control the robot and acquire data from sensors, and another for the BCI), an industrial camera for the localization task, and two Hokuyo laser range finders for obstacle detection. An inertial measurement unit is currently used to estimate the wheelchair dynamic, though we are confident it can be replaced by rotation sensors on the chair wheels; work is in progress. The low-power computer runs the main software; in particular, the sensing modules acquire the sensor and input data (e.g., the joystick signals, the commands coming from the BCI system or from the touchscreen), the reasoning module elaborates the information and determines the wheelchair behavior, and the acting module generates the appropriate commands to control the wheelchair. As the computers rely on wheelchair batteries for power, special low-power custom designs were used.

We are developing a menu-based interface for the control panel of the wheelchair (see Figure 3 for an example) that presents the user with a choice of possible destinations, depending on the contest. The choices can be single rooms or particular positions within the room, e.g., near the table, near the window... When the wheelchair is located within a room, the available choices are the particular locations within the same room, plus all the other rooms of the house/environment. In this way, a hierarchy of location choices can be navigated while the wheelchair physically navigates the environment.

We already did experiments to detect P300s and ErrPs in EEG recordings [9]. Ten (healthy) volunteers participated in two kinds of experiments, where they were asked to interact with a computer while their EEG activity was recorded. In a setup, users operated a simple interface through a keyboard (like in [10]): the user is supposed to fill one of two

bars displayed on the screen by pressing one of two buttons. Each bar is composed by ten parts, and every time the user press a button, the next part get filled, according to the button pressed; and when either bar is full, the trial ends. The user is free to choose either left or right, but the interface is programmed so that with a probability of 20% the wrong bar grows. An analysis of the EEG recordings showed that in three out of five cases an ErrP was detectable with good accuracy (80% accuracy for both error and correct cases).

In a second kind of experiment, subjects used a P300-based BCI, the *P3 speller* [11]. This BCI permits to spell words by selecting one letter at a time. A 6×6 grid of letters and symbols is presented to the user, and entire columns or rows are flashed one after the other in random order. Each one of the 6 rows and 6 columns is flashed exactly once in the first 12 stimulations; then another round of 12 stimulations is repeated, with flashing of rows and columns done in a new random order, and this procedure is repeated for a predefined number of times for each letter. After the fifth repetition, the P300 system detects the row and the column that are more likely to have elicited a P300, and selects the letter at their intersection. The selected letter is presented to the user in the rectangular frame, and it is also concatenated to the text being written. For P300 detection the genetic algorithm (GA) described in [12] was employed. Very briefly, the GA searches the features with which a given classifier perform best. We used features that can be written as the cross-correlation of the EEG signals with some simple templates, and a logistic classifier. This choices has permitted to combine feature extraction with classification, so the computational requirement for P300 detection is very low. The GA accuracy was sufficiently high to give the possibility to five out of seven subjects to make use of such an interface (accuracy in the range 50–90% for a 36-symbol matrix, at a rate of about 4 letter per minute). It is important to notice that by increasing the number of repetitions also the accuracy increases, and hence all subjects should be able to use the interface. Moreover, the experiment aimed at verifying that errors made by the BCI in recognizing the letter selected by the users induced an ErrP in them. The BCI selected the right letter with a probability of 80%, and the wrong one with a probability of 20%; the wrong selection elicited an ErrP in all users, and the automatic detection of ErrPs resulted to be possible in most of them (accuracy between 70% and 90% for both classes).

4. Conclusions and Future Work

We are integrating the wheelchair control system with a full six-degrees-of-freedom SLAM (Simultaneous Localization And Mapping) system based on a monocular frontal camera. SLAM permits to build and continuously update a 3-dimensional map of the surrounding environment. The use of three dimensions is important to avoid collision with low-hanging objects (and even tables, which appear to 2D sensors as just four legs), while the continuous update is useful to avoid moving obstacles.

The idea of integrating a BCI in a smart wheelchair has already appeared in the literature, but some differences with our work should be highlighted. For example, the Maia project is a European project which aims at developing an EEG-based BCI for controlling an autonomous wheelchair [13]. Behaviors like obstacle avoidance and wall following are built in the autonomous control of the wheelchair, while the user just gives simple commands like “go straight”, “go left”. Motor imagery [5] is used by the Maia BCI to drive the wheelchair, haptic feedback is given to the user, and the detection of

error potentials in the user helps to lower the global error rate of the system. The main difference with our system is that the user must continuously drive the wheelchair, and no a-priori map of the environment is provided.

At the National University of Singapore a wheelchair controlled through a P300-based BCI is under development [14]. The wheelchair is autonomous, but its movements are constrained to predefined paths; the user selects a destination and the chair drives there. If an unexpected situation occurs, the wheelchair stops and waits until the user decides what to do. Classification of P300 events is done by a support vector machine fed with samples of the recorded EEG and its time derivative. This project has some resemblance to ours, but our focus is more on a versatile and reusable system than a single application. With respect to P300 detection, our methods are different and try to adapt automatically to the difficulty level of the task; regarding the wheelchair application, the integration with SLAM in our project should provide more flexibility.

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