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Smart Wheel Chair using Neuro – Sky Sensor

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Abstract: The goal of this project is to measure electric activity in the brain due to firing of the neurons, parse wave to obtain attention and meditation level of brain and using it to move a Wheel Chair. The interactions between neurons create an electric discharge which cannot be measured using current technology. There are different techniques available to detect electric activity in brain. One technique is Electroencephalography (EEG). EEG measures voltage fluctuation along the scalp that results from the interaction between the neurons in the brain. These voltage fluctuations are processed and output to a microcontroller by the EEG sensor. The data packets obtained from the EEG sensor are stored in microcontroller. The attention and meditation levels are obtained from the processed data. These levels are used to control the direction and motion of the Wheel Chair.

Keywords: Electro Encephalo Gram, Brain Computer Interface, Canonical Variate Analysis.

I. INTRODUCTION

Millions of people around the world suffer from mobility impairments and hundreds of thousands of them rely upon powered wheelchairs to get on with their activities of daily living. However, many patients are not prescribed powered wheelchairs at all, either because they are physically unable to control the chair using a conventional interface, or because they are deemed incapable of driving safely.

In our work with brain–actuated wheelchairs, we target a population who are—or will become—unable to use conventional interfaces, due to severe motor–disabilities. Non-invasive brain–computer interfaces (BCIs) offer a promising new interaction modality, that does not rely upon a fully– functional peripheral nervous system to mechanically interact with the world and instead uses the brain activity directly. However, mastering the use of a BCI, like with all new skills, does not come without a few challenges. Spontaneously performing mental tasks to convey one's intentions to a BCI can require a high level of concentration, so it would result in a fantastic mental workload, if one had to precisely control every movement of the wheelchair. Furthermore, due to the noisy nature of brain signals, we are currently unable to achieve the same information rates that you might get from a joystick, which would make it difficult to wield such levels of control even if one wanted to.

In this paper, we describe the overall robotic architecture of our brain–actuated wheelchair. We begin by discussing the brain computer interface, since the human is central to our design philosophy. Then, the wheelchair hardware and modifications are described, before we explain how the shared control system fuses the multiple information sources in order to decide how to execute appropriate manoeuvres in cooperation with the human operator. Finally, we present the results of an experiment involving four healthy subjects and compare them with those reported on other brain–actuated wheelchairs. We find that our continuous control approach offers a very good level of performance, with experienced BCI wheelchair operators achieving a comparable performance to that of a manual benchmark condition.

II. BRAIN COMPUTER INTERFACES (BCI) IMPLEMENTATION

A Brain Computer Interface (BCI) is any system which can derive meaningful information directly from the user's brain activity in real time. The most important applications of the technology are mainly meant for the paralyzed people who are suffering from severe neuromuscular disorders. Most BCIs use information obtained from the user's encephalogram (EEG), though BCIs based on other brain imaging methods are possible. This section briefly describes several EEG-based BCIs. The P300 BCI is described in detail in next section.

Brain-Computer Interfaces are generally developed as a rehabilitation tool for locked-in people. Yet research is often conducted with healthy subjects, mostly forpractical reasons. In this section we will review the few papers that cover tests with severely disabled people. One of the earliest study is by Birbaumer in year 2000, which showed that five patients suffering from end-stage ALS could use the TTD (introduced in Section 2.2.1). In 2003 six other patients confirmed those results [29]. Motor imagery based BCIs were also shown to work with severely disabled patients. Pfurtscheller and Neuper showed in 2001 that a C4/C5 tetraplegic patient could control the opening and closing of a hand orthosis [49]. In 2003, a patient with Severe Cerebral Palsy (SCP) could spell letters at a rate of one letter per minute [50]. And in 2005, four people severely disabled by ALS learned to operate such a BCI [51]. Recently, Sellers and colleagues evaluated a P300 BCI with ALS patients. In [52, 53] six ALS patients were trained and tested. They obtained similar classification results as non-ALS patients. Moreover, the study shows that those performances can sustain over several months without degradation

Since we are interested in detecting motor imagery, we acquire monopole EEG at a rate of 512Hz from the motor

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cortex using 16 electrodes (see Fig. 1). The electrical activity of the brain is diffused as it passes through the skull, which results in a spatial blur of the signals, so we apply a Laplacian filter, which attenuates the common activity between neighbouring electrodes and consequently improves our signal to noise ratio.

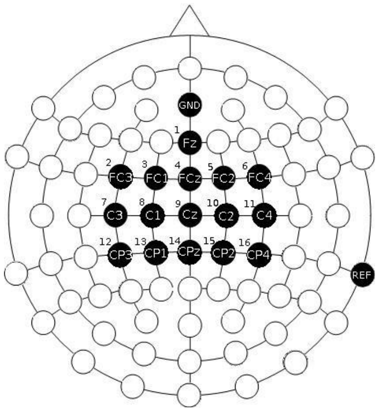


Fig. 1: The active electrode placement over the motor cortex for the acquisition of EEG data based on the International 10-20 system (nose at top).

After the filtering, we estimate the power spectral density (PSD) over the last second, in the band 4–48Hz with a 2Hz resolution [8]. It is well know that when one performs motor imagery tasks, corresponding parts of the motor cortex are activated, which, as a result of event related desynchronisation, yields a reduction in the mu band power (~8–13Hz) over these locations (e.g. the right hand corresponds to approximately C1 and the left hand to approximately C2 in Fig. 1). In order to detect these changes, we estimate the PSD features every 62.5 ms (i.e. 16 times per second) using the Welch method with 5 overlapped (25%) Hanning windows of 500 ms.

Every person is different, so we have to select the features that best reflect the motor–imagery task for each subject. Therefore, canonical variate analysis (CVA) is used to select subject–specific features that maximize the separability between the different tasks and that are most stable (according to cross validation on the training data) [9]. These features are then used to train a Gaussian classifier [10]. Decisions with a confidence on the probability distribution that are below a given rejection threshold are filtered out. Finally, evidence about the executed task is accumulated using an exponential smoothing probability integration framework [11]. This helps to prevent commands from being delivered accidentally.

III. NEUROSKY SENSOR

The MindWave Mobile headset turns your computer into a brain activity monitor. The headset safely measures brainwave signals and monitors the attention levels of individuals as they interact with a variety of different apps. This headset is useful for OEMs and developers building apps for health and wellness, education and entertainment.

The MindWave family consists of MindWave and MindWave Mobile headsets. The MindWave is designed for PCs and Mac, while the MindWave Mobile is compatible with PCs, Mac and mobile devices like the iPhone, iPad, and Android. If you want a mobile compatible device, check out the MindWave Mobile. Both headsets share the following characteristics.

The NeuroSky ThinkGear ASIC chip is priced to power mass adoption in health and wellness, educational and entertainment devices, popular EEG technology.

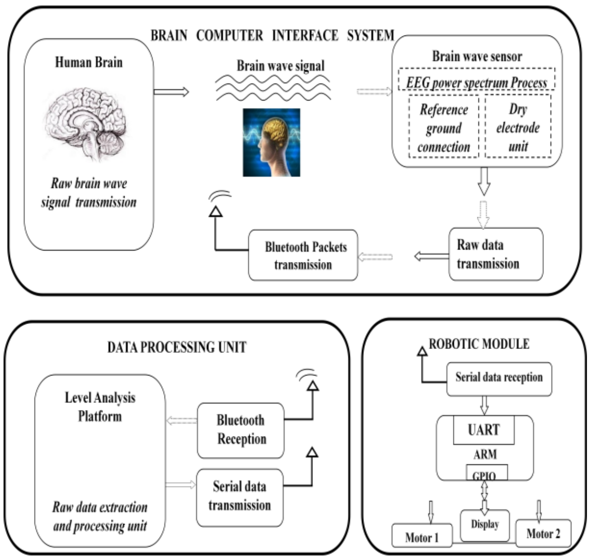
III.WHEELCHAIR HARDWARE

Our brain–controlled wheelchair is based upon a commercially available mid–wheel drive model by Invacare that we have modified. First, we have developed a remote joystick module that acts as an interface between a laptop computer and the wheelchair's CANBUS–based control network. This allows us to control the wheelchair directly from a laptop computer. Second, we have added a pair of wheel–encoders to the central driving wheels in order to provide the wheelchair with feedback about its own motion. Third, an array of ten sonar sensors and two webcams have been added to the wheelchair to provide environmental feedback to the controller.

Fourth, we have mounted an adjustable 8" display to provide visual feedback to the user. Fifth, we have built a power distribution unit, to hook up all the sensors, the laptop and the display to the wheelchair's batteries. The complete BCI wheelchair platform is shown in Fig. 2. The positions of the sonars are indicated by the white dots in the centre of the occupancy grid, whereas the two webcams are positioned forward–facing, directly above each of the front castor wheels.

A. Wheel–encoders

The encoders return 128 ticks per revolution and are geared up to the rim of the drive wheels, resulting in a resolution of $2.75\times10{-}3$ metres translation of the inflated drive wheel per encoder tick. We use this information to calculate the average velocities of the left and right wheels for each time–step. Not only is this important feedback to regulate the wheelchair control signals, but we also use it as the basis for dead reckoning (or estimating the trajectory that has been driven).



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We apply the simple differential drive model derived in [12]. To ensure that the model is always analytically solvable, we neglect the acceleration component. In practice, since in this application we are only using the odometry to update a 6m×6m map, this does not prove to be a problem. However, if large degrees of acceleration or slippage occur and the odometry does not receive any external correcting factors, the model will begin to accumulate significant errors.

IV. SHARED CONTROL ARCHITECTURE

The job of the shared controller is to determine the meaning of the vague, high–level user input (e.g. turn left, turn right, keep going straight), given the context of the surrounding environment .
We do not want to restrict ourselves to a known, mapped environment—since it may change at any time (e.g. due to human activities)—so the wheelchair must be capable of perceiving its surroundings. Then, the shared controller can determine what actions should be taken, based upon the user's input, given the context of the surroundings.
The overall robotic shared control architecture is depicted in Fig. 3 and we discuss the perception and planning blocks of the controller over the next few subsections.

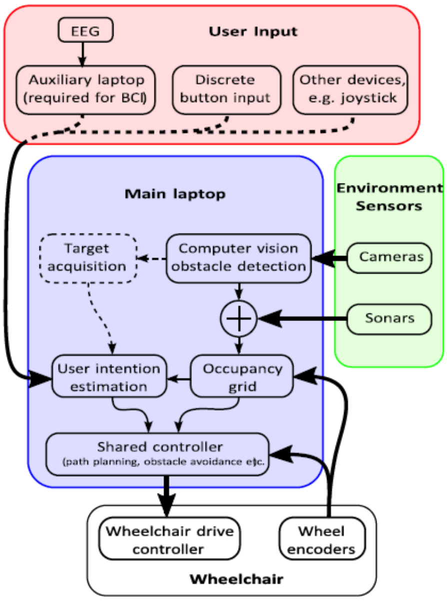

Fig. 3: The user's input is interpreted by the shared controller given the context of the surroundings. The environment is sensed using a fusion of complementary sensors, then the shared controller generates appropriate control signals to navigate safely, based upon the user input and the occupancy grid.

A. PERCEPTION

Unlike for humans, perception in robotics is difficult. To begin with, choosing appropriate sensors is a not a trivial task and tends to result in a trade–off between many issues, such as: cost, precision, range, robustness, sensitivity, complexity of post-processing and so on. Furthermore, no single sensor by itself seems to be sufficient. For example, a planar laser scanner may have excellent precision and range, but will only detect a table's legs, reporting navigable free space between them. Other popular approaches, like relying solely upon cheap and readily available sonar sensors have also been shown to be unreliable for such safety–critical applications [14]. To overcome these problems, we propose to use the synergy of two low–cost sensing devices to compensate for each other's drawbacks and complement each other's strengths. Therefore, we use an array of ten close–range sonars, with a wide detection beam, coupled with two standard off–the–shelf USB webcams, for which we developed an effective obstacle detection algorithm. We then fuse the information from each sensor modality into a probabilistic occupancy grid, as will be discussed in Section IV-C.

B. COMPUTER VISION–BASED OBSTACLE DETECTION

The obstacle detection algorithm is based on monocular image processing from the webcams, which ran at 10Hz. The concept of the algorithm is to detect the floor region and label everything that does not fall into this region as an obstacle; we follow an approach similar to that proposed in [13], albeit with monocular vision, rather than using a stereo head.
The first step is to segment the image into constituent regions. For this, we use the watershed algorithm, since it is fast enough to work in real–time [15]. We take the original image (Fig 4a) and begin by applying the well–known Canny edge–detection, as shown in Fig. 4b. A distance transform is then applied, such that each pixel is given a value that represents the minimum Euclidean distance to the nearest edge. This results in the relief map shown in Fig. 4c, with a set of peaks (the farthest points from the edges) and troughs (the edges themselves). The watershed segmentation algorithm itself is applied to this relief map, using the peaks as markers, which results in an image with a (large) number of segments (see Fig. 4d). To reduce the number of segments, adjacent regions with similar average colours are merged. Finally, the average colour of the region that has the largest number of pixels along the base of the image is considered to be the floor. All the remaining regions in the image are classified either as obstacles or as navigable floor, depending on how closely they match the newly–defined floor colour. The result is shown in Fig. 4e, where the detected obstacles are highlighted in red.
Since we know the relative position of the camera and its lens distortion parameters, we are able to build a local occupancy grid that can be used by the shared controller, as is described in the following section.

(a) Original Image

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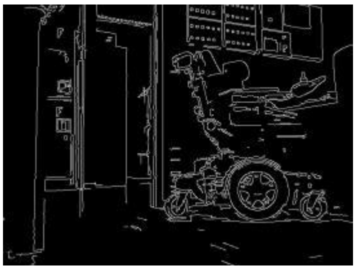

(b) Edge Detection

(c) Distance Transform

(d) Watershed Segmentation

(e) Detected Obstacles

C. UPDATING THE OCCUPANCY GRID

At each time–step, the occupancy grid is updated to include the latest sample of sensory data from each sonar and the output of the computer vision obstacle detection algorithm. We extend the histogram grid construction method described in [16], by fusing information from multiple sensor types into the same occupancy grid. For the sonars, we consider a ray to be emitted from each device along its sensing axis. The likelihood value of each occupancy grid cell that the ray passes through is decremented, whilst the final grid cell (at the distance value returned by the sonar) is incremented. A similar process is applied for each column of pixels from the computer vision algorithm, as shown in Fig. 5. The weight of each increment and decrement is determined by the confidence we have for each sensor at that specific distance. For example, the confidence of the sonar readings being correct in the range 3cm to 50cm is high, whereas outside that range it is zero (note that the sonars are capable of sensing up to 6m, but given that they are mounted low on the wheelchair, the reflections from the ground yield a practical limit of 0.5m). Similarly, the computer vision algorithm only returns valid readings for distances between 0.5m and 3m. Using this method, multiple sensors and sensor modalities can be integrated into the planning grid.

As the wheelchair moves around the environment, the information from the wheel–encoder based dead–reckoning system is used to translate and rotate the occupancy grid cells, such that the wheelchair remains at the centre of the map. In this way, the cells accumulate evidence over time from multiple sensors and sensor modalities. As new cells enter the map at the boundaries, they are set to “unknown”, or 50% probability of being occupied, until new occupancy evidence (from sensor readings) becomes available.

D. MOTION PLANNING

All the motion planning is done at the level of the occupancy grid, which integrates the data from multiple sensors. We base our controller on a dynamical system approach to navigation, since this easily allows us to incorporate the notion of obstacles (repellers) and targets (attractors), and results in naturally smooth trajectories [17]. Previously, we have implemented.

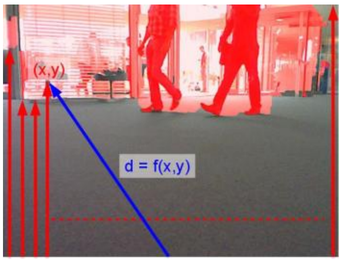

Fig. 5: Each column of pixels is scanned from bottom to top, in order to detect the nearest obstacle (assuming it intersects with the ground).

V. EVALUATION

We demonstrate that both naıve and experienced BCI wheelchair operators are able to complete a navigation task successfully. Furthermore, unlike in P300–based systems, not only was the user in continuous spontaneous control of the wheelchair, but the resultant trajectories were smooth and intuitive (i.e. no stopping, unless there was an obstacle, and users could voluntarily control the motion at all times).

A. PARTICIPANTS

Mastering a motor imagery BCI requires extensive training, over a period of weeks or months to generate stable volitional control; it is not simply a case of putting a cap on and starting to drive. Therefore, we have performed an initial evaluation with four healthy male subjects, aged 23–28. All subjects were experienced BCI users, who had participated in at least 12 hours of online motor imagery BCI training and other BCI experiments over the previous few months. They all had some previous experience of driving a BCI– based tele–presence mobile robot, which requires a better level of performance, compared to simply moving a cursor on a screen [18]. Subjects’ s1 and s2 had

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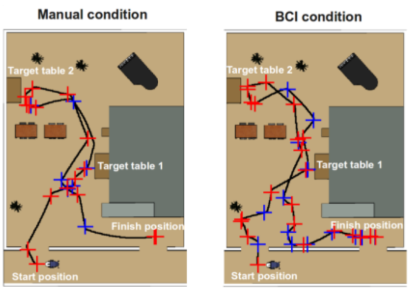
no previous experience of driving a BCI–controlled wheelchair, whereas subjects' s3 and s4 had each clocked–up several hours of driving the BCI wheelchair. Subject s1 used motor imagery of both feet to indicate turn left and of the right hand to mean turn right; all the other subjects used left hand motor imagery to turn left and right hand motor imagery to turn right.

B. EXPERIMENT PROTOCOL

As a benchmark, the subject was seated in the wheelchair and was instructed to perform an online BCI session, before actually driving. In this online session, the wheelchair remained stationary and the participant simply had to perform the appropriate motor imagery task to move a cursor on the wheelchair screen in the direction indicated by a cue arrow. There was a randomized balanced set of 30 trials, separated by short resting intervals, which lasted around 4– 5mins, depending on the performance of the subject.

After the online session, participants were given 15–30 minutes to familiarise themselves with driving the wheelchair using each of the control conditions: a two button manual input, which served as a benchmark, and the BCI system. Both input paradigms allowed the users to issue left and right commands at an inter–trial interval of one second.

The actual task was to enter a large open–plan room through a doorway from a corridor, navigate to two different tables, whilst avoiding obstacles and passing through narrow openings (including other non–target tables, chairs, ornamental trees and a piano), before finishing by reaching a second doorway exit of the room (as shown in Fig 7). When approaching the target tables, the participants were instructed to wait for the wheelchair to finish docking to the table, then once it had stopped they should issue a turning command to continue on their journey. The trials were counter–balanced, such that users began with a manual trial, then performed two BCI trials and finished with another manual trial.



C. RESULTS AND DISCUSSION

All subjects were able to achieve a remarkably good level of control in the stationary online BCI session, as can be seen in Table I. Furthermore, the actual driving task was completed successfully by every subject, for every run and no collisions occurred. A comparison between the typical trajectories followed under the two conditions is shown in Fig 7. The statistical tests reported in this section are paired Student's t-tests.

A great advantage that our asynchronous BCI wheelchair brings, compared with alternative approaches like the P300– based chairs, is that the driver is in continuous control of the wheelchair. This means that not only does the wheelchair follow natural trajectories, which are determined in real–time by the user (rather than following predefined ones, like in [5]), but also that the chair spends a large portion of the navigation time actually moving (see Fig. 8). This is not the case with some state–of–the–art P300–controlled wheelchairs, where the wheelchair has to spend between 60% and 80% of the manoeuvre time stationary, waiting for input from the user (c.f. Fig. 8 of this article with Fig. 8 of [6]).

In terms of path efficiency, there was no significant difference ($p = 0.6107$) across subjects between the distance travelled in the manual benchmark condition (43.1±8.9m) and that in the BCI condition (44.9±4.1m). Although the actual environments were different, the complexity of the navigation was comparable to that of the tasks investigated on a P300– based wheelchair in [6]. In fact, the average distance travelled for our BCI condition (44.9±4.1m), was greater than that in the longest task of [6] (39.3±1.3m), yet on average our participants were able to complete the task in 417.6±108.1s, which was 37% faster than the 659±130s reported in [6]. This increase in speed might (at least partly) be attributed to the fact that our wheelchair was not stationary for such a large proportion of the trial time.

VI. CONCLUSION

In this article, we have seen how a viable brain–actuated wheelchair can be constructed by combining a brain computer interface with a commercial wheelchair, via a shared control layer. The shared controller couples the intelligence and desires of the user with the precision of the machine. We have found that this enabled both experienced and inexperienced users alike to safely complete a driving task that involved docking to two separate tables along the way.

Furthermore, we have compared our results with those published on other state–of–the–art brain–controlled wheelchairs that are based on an alternative synchronous stimulus–driven protocol (P300). Our asynchronous motor–imagery approach gives users greater flexibility and authority over the actual trajectories driven, since it allowed users to interact with the wheelchair spontaneously, rather than having to wait for external cues as was the case with [5], [6].

Moreover, combining our BCI with a shared control architecture allowed users to dynamically produce intuitive and smooth trajectories, rather than relying on predefined routes [5] or having to remain stationary for the majority of the navigation time [6].

Although there was a cost in terms of time for inexperienced users to complete the task using the BCI input compared with a manual benchmark, experienced users were able to complete the task in comparable times under both conditions. This is probably as a result of them developing good mental models of how the coupled BCI–shared control system behaves.

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In summary, the training procedure for spontaneous motor imagery–based BCIs might take a little longer than that for stimulus–driven P300 systems, but ultimately it is very rewarding. After learning to modulate their brain signals appropriately, we have demonstrated that both experienced and inexperienced users were able to master a degree of continuous control that was sufficient to safely operate a wheelchair in a real world environment.

They were always successful in completing a complex navigation task using mental control over long periods of time. One participant remarked that the motor–imagery BCI learning process is similar to that of athletes or musicians training to perfect their skills: when they eventually succeed they are rewarded with a great sense of self–achievement.

VII. FUTURE ENHANCEMENT

In future, it is improved by sensing the movement eyeballs through **"Blue Brain Technology".** The destination can be reached by seeing the location once where the user wants to move.

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