

# The Birth of the Brain–Controlled Wheelchair

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**Abstract**—The prospect of controlling devices merely by the power of one’s thoughts is compelling, especially for assistive technology applications. In the accompanying video, we show how we have strived to push brain–computer interface (BCI) technology out of the lab and into the real world, while simultaneously moving away from testing solely with healthy subjects to undertaking trials with patients and potential end–users. We describe the evolution of the motor imagery based BCI, which has resulted in a major milestone: the first patient trial of a motor imagery based BCI controlled wheelchair.

## I. INTRODUCTION

The Defitech Foundation Chair in Non-Invasive Brain-Machine Interface (CNBI) performs research on the use of human brain signals to control devices and software in order to interact with the world. In this multidisciplinary area of research, we draw upon our expertise in the the fields of brain-computer interfaces (BCI) and adaptive intelligent robotics. Our goal is to develop intelligent brain–actuated devices that people can efficiently operate in a natural and intuitive manner, over extended periods of time. Our brain–actuated wheelchair is a flagship example of our efforts to date and in the accompanying short film, we document its brief history.

We begin by explaining the basic operating principles of our motor-imagery based BCI. Then we reflect on the milestones reached over the past 14 years. Throughout this period we have been steadily pushing BCI technology in two directions. Firstly, we have been striving to move it out of the lab and into the real world. Secondly, we have been committed to transferring the testing of the technology from scientists and able–bodied subjects to patients, therapists and potential end–users.

## II. THE BRAIN COMPUTER INTERFACE

Our BCI, which is based on the imagination of movements, is best conceptualised as a loop. We begin by recording the electrical activity of the brain using scalp electrodes, which is known as electroencephalography (EEG). Since the brain signals are very weak and spread out as they pass through the skull, we need to apply some spatial and spectral filters to the EEG to extract characteristic features. Using machine learning techniques, we are then able to discriminate between different mental tasks, such as the imagination of left or right hand movements. A number of these mental tasks can then be associated with control commands. For example, the imagination of left hand movement could indicate “turn

left”, and similarly, right hand motor imagery could be mapped to a “turn right” command. Once a command has been executed, the user receives feedback and thus the loop begins again.

## III. BRAIN–CONTROLLED DEVICES

Although EEG–based BCIs are improving in terms of accuracy, reliability and speed, they can pose a challenge if one wishes to directly control a device for a prolonged period of time. In the following few sections we describe the milestones we have reached (in terms of moving the BCI out of the lab and into the real world, away from healthy test subjects and to patients and potential end–users) and the evolution of techniques, such as shared control [1], which have enabled us to overcome such challenges. Ethical approval was granted by the relevant local committees for each of the reported studies.

### A. Simple Games

Once we were able to successfully discriminate between different patterns of brain activity, we wanted to see if people could learn to modulate their brain signals and use them as a new interaction modality. Initially we tested our hypothesis by associating different mental tasks with commands that would move a cursor on a screen. However, this is not a particularly engaging experience, so we soon started exploring the possibility of playing simple games. In the accompanying video, we show clips of the game “Sisyphus”, where the user had to perform motor imagery tasks in order to roll a cartoon boulder up a hill [2]. The game was a useful training tool that provided motivating feedback. Later, we were also able to play the well–know game Pacman, by using our BCI to issue discrete turning commands to the left and right [2].

### B. Miniaturised Robots and Mazes

As already mentioned, our goal was to move BCIs from the laboratory environment into the real world, so we began to investigate more complex types of interaction. We showed that we can use our BCI to directly control a tiny behaviour–based robot and consequently navigate around a physical maze [3]. To drive the robot, the user only needed to issue high–level commands to change the behaviour of the robot (e.g. turn left, move forward). The behaviour–based controller guaranteed obstacle avoidance and smooth turns, based upon its sensor readings. In particular, if the robot deemed a specific mental command to be unsafe, based upon its sensor data, the command would not be executed. This asynchronous approach to BCI control proved to be sufficient

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to continuously manoeuvre the mobile robot along non-trivial trajectories, which required fast and frequent switches between the mental tasks. Two able-bodied subjects were able to mentally drive the robot in a house-like environment, moving between rooms as instructed [4]. At the same time, we began to investigate, whether we could transfer these BCI skills to the real-time control of a wheelchair, by performing experiments in a simulated virtual reality environment [5].

### C. Brain Controlled Wheelchairs

Driving a real wheelchair safely in more complex environments would be a highly demanding task for a BCI subject, due for example, to the necessity of delivering commands with precise timing. However, shared control techniques—where the intelligent controller relieves the human from low level tasks, without sacrificing the cognitive superiority and adaptability of human beings—have been shown to significantly reduce workload, whilst simultaneously improving task performance [1]. Therefore, shared control principles were incorporated into the first motor-imagery brain controlled wheelchair [6]. In other words, the shared control paradigm includes two intelligent agents: the human user and the robot, such that the user need only convey intentions, which the robot interprets in the current context.

### D. Into the Real World and with Patients

To tackle navigation in the real-world, we moved away from artificially constructed environments to test our wheelchair, but at the same time we faced new challenges. An expensive laser scanner was no longer sufficient to perceive the environment. For example the planar laser scanner might see the legs of a table, but not the surface and consequently, the wheelchair might try to drive straight through it. Therefore, we developed sophisticated computer vision algorithms that worked with off-the-shelf webcams and combined this sensory information with an array of sonars that we fed to our shared control algorithm [7].

Until this point, most of the BCI experiments described above have been performed with healthy subjects. Also, there is a large gap in the learning curve between controlling a cursor on the screen and driving a BCI wheelchair. Therefore, we have further developed our BCI robot in a telepresence framework, such that users can practice driving safely and get used to the notion of shared control, without having to even leave their bed. We have found that on average, six motor disabled patients were able to navigate using our brain-controlled telepresence robot, at least as well as our healthy control subjects and that we could reduce the required cognitive workload [8], [9]

Finally, we have found that a motor-disabled patient in a rehabilitation centre was able to drive our brain-controlled wheelchair at least as well as four healthy subjects [9]. Furthermore, each driving task last between 5 and 10 minutes, which is a considerably long time to be continuously controlling a BCI system.

## IV. CONCLUSION

Our research is based on three core principles for brain-computer interaction. First, we use asynchronous protocols, where subjects decide voluntarily when to switch between mental tasks, which they perform at their own pace, or rest. Second, we employ mutual learning, where machine learning techniques are used to discriminate between different patterns of brain signals and the appropriate feedback is given to the user to help them to form mental models of the system behaviour. Third, we use shared control, where the user conveys high level mental commands to the robot, which interprets and executes them in the most appropriate way to achieve the goal. Through these principles, we have shown that we can successfully push BCI technology out of the lab and into the real world, where we can test not only with healthy subjects, but also with patients and potential end users. Finally we have demonstrated that our BCI wheelchair can be driven successfully by a motor-disabled patient.

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