



Non Invasive Brain-Machine Interfaces Final Report

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Executive Summary

The idea of controlling machines not by manual control, but by mere “thinking” (i.e., the brain activity of human subjects) has fascinated humankind since ever, and researchers working at the crossroads of computer science, neurosciences, and biomedical engineering have started to develop the first prototypes of *brain-computer interfaces (BCI)* over the last decade or so (Dornhege et al., 2006; Millán, 2002; Nicoletis, 2001; Wickelgren, 2003; Wolpaw et al., 2002). Such a kind of BCI is a natural way to augment human capabilities by providing a new interaction link with the outside world and is particularly relevant as an aid for paralyzed humans, although it also opens up new possibilities in human-robot interaction for able-bodied people.

Recently, researchers have been able to train monkeys, who had implanted tens of microelectrodes in their brain, to control a robot arm (Carmena et al., 2003; Mussallam et al., 2004; Serruya et al., 2002; Taylor et al., 2002). For humans, however, non-invasive methods based on EEG signals¹ are preferable because of ethical concerns and medical risks. Despite their poor signal-to-noise ratio, our recent experiments have shown for the first time that EEG is sufficient for humans to continuously control a mobile robot similar to a wheelchair (Millán et al., 2004a, 2004b). Two human subjects learned to drive the robot between rooms in a house-like environment by mental control only. Furthermore, mental control was only marginally worse than manual control on the same task.

In this study we will first review the field of brain-computer interfaces (BCI), with emphasis on non-invasive BCIs as this one is the most promising for space applications. Most non-invasive BCI systems use electroencephalogram (EEG) signals; i.e., the electrical brain activity recorded from electrodes placed on the scalp. Non-invasive EEG-based BCIs can be classified as “evoked” or “spontaneous”. An evoked BCI exploits a strong characteristic of the EEG, the so-called evoked potential, which reflects the immediate automatic responses of the brain to some external stimuli. Evoked potentials are, in principle, easy to pick up with scalp electrodes and two different evoked potentials have been widely explored in the field of BCI, namely *P300* (Allison & Pineda, 2003; Bayliss, 2003; Farwell & Donchin, 1988) and *steady-state visual evoked potential (SSVEP)*. (Gao et al., 2003; Middendorf et al., 2000; Sutter, 1992). The necessity of external stimulation does, however, restrict the applicability of evoked potentials to a limited range of tasks. In our view, a more natural and suitable alternative for interaction is to analyze components associated with spontaneous “intentional” mental activity. This is particularly the case when controlling robotics devices.

Spontaneous BCIs are based on the analysis of EEG phenomena associated with various aspects of brain function related to mental tasks carried out by the subject at his/her own will. Such a kind of BCI can exploit two kinds of spontaneous, or endogenous, brain signals, namely *slow potential shifts* (Birbaumer et al., 1999; Blankertz et al., 2003) or variations of *rhythmic activity* (Anderson, 1997; Babiloni et al., 2000; Birch et al., 2002; Blankertz et al., 2005; Millán, 2003; Millán et al., 2004a, 2004b; Pfurtscheller & Neuper, 1997; 2001; Roberts & Penny, 2000; Wolpaw & McFarland, 2004; Wolpaw et al., 2000). It should be noted that eye movements and breathing may cause considerable artefacts in slow potentials while muscular tension—in face and neck—can generate artefacts in higher frequencies. Also, EEG rhythms have response latencies of about 0.5 seconds whereas other EEG components—e.g., slow potentials and event-related potentials such as P300 and SSVEP—have response latencies of two or more seconds.

A critical issue for the development of a BCI is training—i.e., how users learn to operate the BCI. Some groups have demonstrated that some subjects can learn to control their brain activity through appropriate, but lengthy, training in order to generate fixed EEG patterns that the BCI transforms into external actions (Birbaumer et al., 1999; Wolpaw et al., 2000). In this case the subject is trained over several months to modify the amplitude of their EEG signals. Other groups follow machine-learning approaches to train the classifier embedded in the BCI (Anderson, 1997; Blankertz et al., 2003; Millán et al., 2004a, 2004b;

¹ The electroencephalogram (EEG) is the brain electrical activity recorded from electrodes placed on the scalp.

Pfurtscheller and Neuper, 2001; Roberts and Penny, 2000). Most of these approaches are based on a mutual learning process where the user and the brain interface are coupled together and adapt to each other. This should accelerate the training time.

After reviewing other issues such as operational protocols (synchronous or asynchronous) and ways to improve the quality of the EEG signals (in particular, spatial filters), we will describe some of the current applications of BCI that augment people's communication capabilities (Birbaumer et al., 1999; Farwell & Donchin, 1988; Millán, 2003; Millán et al., 2004a; Obermaier et al., 2003; Scherer et al., 2004; Wolpaw et al., 2000), provide new forms entertainment (Millán, 2003), and also enable the operation of physical devices (Millán et al., 2004a, 2004b; Pfurtscheller & Neuper, 2001). Then, we will discuss some foreseen improvements necessary for bringing BCI technology out of the lab. In this respect, a critical issue is how to improve the robustness of BCIs with the goal of making it a more practical and reliable technology.

Finally, we will discuss possible applications of BCIs in the space environment, where astronauts are subject to extreme conditions and could greatly benefit from direct mental teleoperation of external semi-automatic manipulators or robotic agents—for instance, mental commands could be sent without any output/latency delays, as it is the case for manual control in microgravity conditions. Such space applications will range from critical, and non-critical, robotic applications to environment control and even to monitoring astronauts' cognitive state.

1. Introduction

There is a growing interest in the use of brain signals for communication and operation of devices, in particular for physically disabled people. Brain states can be detected and translated into actions such as selecting a letter from a virtual keyboard, playing a video game, or moving a robot arm (Birbaumer et al., 1999; Blankertz et al., 2005; Carmena et al., 2003; Chapin et al., 1999; Farwell & Donchin, 1988; Kennedy et al., 2000; Millán, 2003; Millán et al., 2004a, 2004b; Mussallam et al., 2004; Obermaier et al., 2003; Pfurtscheller & Neuper, 2001; Scherer et al., 2004; Serruya et al., 2002; Taylor et al., 2002; Wolpaw & McFarland, 2004; Wolpaw et al., 2000). Such devices, which do not require the user to perform any physical action, are called *brain-computer interfaces (BCI)* or *brain-machine interfaces*¹ (for reviews see (Dornhege et al., 2006; Millán, 2002; Nicolelis, 2001; Wickelgren, 2003; Wolpaw et al., 2002)). It is worth noting that, although BCI prototypes have only been developed recently, the basic ideas were already put forward in the 1970s. Initial successful experiments were based on the analysis of brain electrical activity—the visual evoked potential—generated in response to changes in gaze direction (Vidal, 1977) (see also (Gao et al., 2003; Middendorf et al., 2000; Sutter, 1992)).

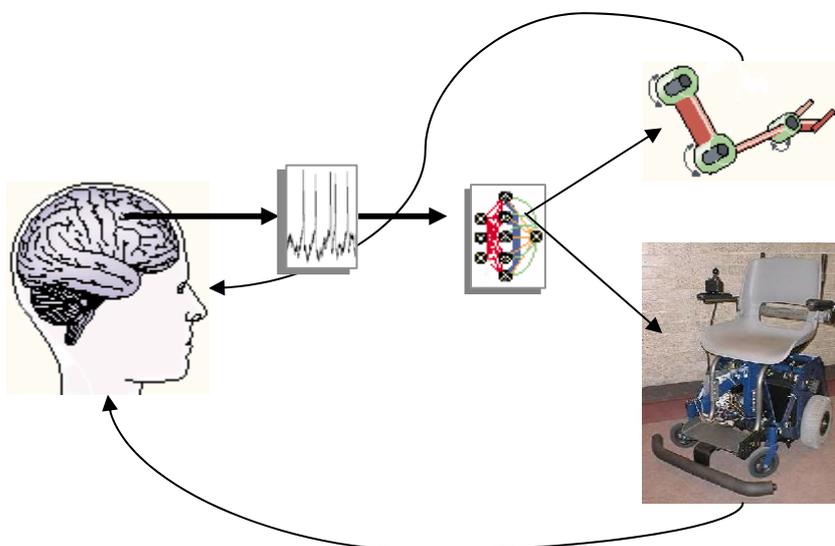


Figure 1: General architecture of a brain-computer interface for controlling robotics devices

Such a kind of BCI is a natural way to augment human capabilities by providing a new interaction link with the outside world and is particularly relevant as an aid for paralyzed humans, although it also opens up new possibilities in human-robot interaction for able-bodied people. Figure 1

¹ Although brain-computer interfaces (BCI) and brain-machine interfaces (BMI) refer to the same general kind of interface technology, it is agreed that the latter are based upon invasive signals whereas the former relies upon non-invasive signals. For this reason the term BCI will be used in this report.

shows the general architecture of a brain-actuated robot. Brain electrical activity is recorded with a portable device. These raw signals are first processed and transformed in order to extract some relevant features that are then passed on to some mathematical models (in principle, neural networks). This model computes, after some training process, the appropriate mental commands to control robotic devices, from robot arms to vehicles. Finally, visual feedback, and maybe other kinds such as haptic stimulation, informs the subject about the performance of the brain-actuated robot so that she can learn appropriate mental control strategies and make rapid changes to achieve the task.

A BCI may monitor brain activity via a variety of methods, which can be coarsely classified as invasive and non-invasive. Most non-invasive BCI systems use electroencephalogram (EEG) signals; i.e., the electrical brain activity recorded from electrodes placed on the scalp. The main source of the EEG is the synchronous activity of thousands of cortical neurons. Measuring the EEG is a simple noninvasive way to monitor electrical brain activity, but it does not provide detailed information on the activity of single neurons (or small brain areas). Moreover, it is characterized by small signal amplitudes (a few μ Volts) and noisy measurements (especially if recording outside shield rooms).

Besides electrical activity, neural activity also produces other types of signals, such as magnetic and metabolic, that could be used in a BCI. Magnetic fields can be recorded with magnetoencephalography (MEG), while brain metabolic activity—reflected in changes in blood flow—can be observed with positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging. Unfortunately, such alternative techniques require sophisticated devices that can be operated only in special facilities. Moreover, techniques for measuring blood flow have long latencies and thus are less appropriate for interaction.

In invasive BCI systems the activity of single neurons (their spiking rate) is recorded from microelectrodes implanted in the brain. In a series of experiments with rats and monkeys, researchers have monitored different areas of the cortex related to execution and planning of movements—motor, premotor and posterior parietal cortex. From a real-time analysis of the activity of the neuronal population, it has been possible to determine the animal's movement intention (Chapin et al., 1999; Mussallam et al., 2004), predict the monkey's hand trajectory (Carmena et al., 2003; Taylor et al., 2002), and to drive a computer cursor to desired targets (Serruya et al., 2002; Taylor et al., 2002). In human patients, first steps towards invasive approaches have been made (Kennedy et al., 2000) **Error! Reference source not found.** One of the patients was eventually able to drive a cursor and write messages. His performance, however, was similar to that achieved with noninvasive BCI systems (Millán, 2002). Less invasive approaches are based on the analysis of electrocorticogram (ECoG) signals from electrodes implanted under the skull (Grimm et al., 2003; Leuthardt et al., 2004). ECoG signals are less noisy than EEG signals and have also a higher spatial resolution. The former, however, still requires surgical operations.

Given the risks generated by permanent surgically implanted devices in the brain, and the associated ethical concerns, we will concentrate in the sequel only on non-invasive approaches, in particular electrical brain signals as measured by EEG.

2. EEG-based Brain-Computer Interfaces: Methodologies

For certain stimuli, such as flashed images and lights, the EEG exhibits a strong characteristic signal, the so-called evoked potential, which reflects the immediate automatic responses of the brain to those external stimuli. Evoked potentials are, in principle, easy to pick up with scalp electrodes and have been used in the context of BCIs (Allison & Pineda, 2003; Bayliss, 2003; Farwell & Donchin, 1988; Gao et al., 2003; Middendorf et al., 2000; Sutter, 1992). The necessity of external stimulation does, however, restrict the applicability of evoked potentials to a limited range of tasks. In our view, a more natural and suitable alternative for interaction is to analyze components associated with spontaneous “intentional” mental activity. This is particularly the case when controlling robotics devices.

2.1 Evoked BCIs

Evoked BCIs depend on the brain’s response to external events. Two different evoked potentials have been widely explored in the field of BCI, namely *P300* and *steady-state visual evoked potential (SSVEP)*.

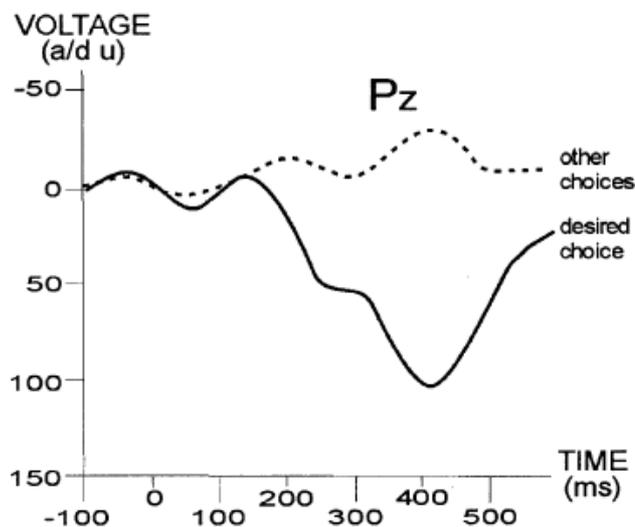


Figure 2: Grand average evoked potentials across many trials and subjects over the Pz electrode. Time 0 is stimulus onset. Note the large P300 peak (actually happening at around 400 ms) for the desired infrequent choice that does not appear for undesired choices.

P300 is a potential evoked by an awaited infrequent event that appears at centro-parietal locations along the midline of the scalp (see Section 2.3 for details of EEG electrodes placement). As illustrated in Figure 2, it is a positive wave peaking at around 300 ms after task-relevant stimuli. The amplitude of the P300 depends on the frequency of stimulus occurrence—less frequent stimuli produce larger response—and task relevance.

Traditionally, P300 has been used to develop virtual keyboards (Allison & Pineda, 2003; Farwell & Donchin, 1988), but recently this same potential has also been the basis for brain-actuated control of a virtual reality system (Bayliss, 2003) and of a wheelchair (Rebsamen et al., 2006). In order to evoke the P300, subjects are given a sufficiently large number of options (e.g., letters of the alphabet or icons) from which they choose one. Then, options are flashed several times each in a random order. Finally, it is possible to determine which choice the subject intended as a target simply by selecting the stimulus that elicits the largest P300.

Visual evoked potentials (VEP) reflect electrophysiological mechanisms underlying the processing of visual information in the brain and vary in response to changes in visual stimuli. Steady-state visual evoked potentials (SSVEP) are VEP induced by a stimulus repeated at a rate higher than 6 Hz. SSVEP is composed of a series of components whose frequencies are exact integer multiples of the stimulus frequency. In other words, fixating a stimulus flashing at 6-30 Hz evokes a similar rhythm—the SSVEP—in the visual cortex. This implies that SSVEP-based BCIs depend on muscular control of gaze direction for their operation, whereas all other kinds of BCI systems do not depend on the brain's normal output pathways of peripheral nerves and muscles. The principle of operation is then quite simple (Gao et al., 2003; Middendorf et al., 2000; Sutter, 1992). Multiple targets are placed on a visual panel, each flickering at a different frequency. When a subject gazes at a certain target, a SSVEP is induced in the brain whose fundamental frequency is equal to the flickering frequency of the target. Figure 3 shows an example of SSVEPs induced by two different targets. SSVEP is measured at electrodes over the visual cortex back in the scalp; i.e., at occipital locations such as O1 and O2 (see Section 2.3 for details of EEG electrodes placement).

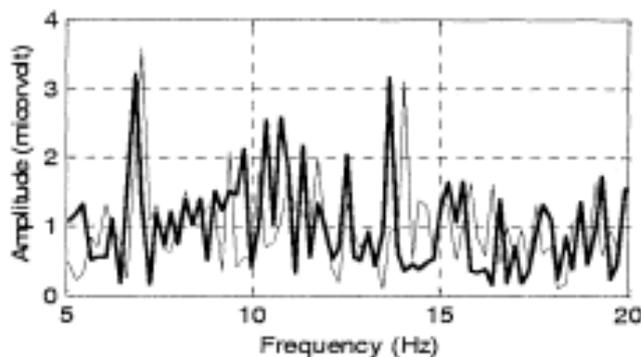


Figure 3: Amplitude spectra of SSVEPs induced by a 6.83-Hz (thick) and a 7.03-Hz (thin) visual stimulation. The peaks at these frequencies, as well as at their second harmonics, are clearly identified (reproduced from (Gao et al., 2003))

2.2 Spontaneous BCI

Spontaneous BCIs are based on the analysis of EEG phenomena associated with various aspects of brain function related to mental tasks carried out by the subject at his/her own will. Such a kind of BCI can exploit two kinds of spontaneous, or endogenous, brain signals, namely slow potential shifts or

variations of rhythmic activity. It should be noted that eye movements and breathing may cause considerable artefacts in slow potentials while muscular tension—in face and neck—can generate artifacts in higher frequencies. Also, EEG rhythms have response latencies of about 0.5 seconds whereas other EEG components—e.g., slow potentials and event-related potentials such as P300 and SSVEP—have response latencies of two or more seconds.

2.2.1 Slow Potentials

Some researchers measure *slow cortical potentials (SCP)*—whose negative amplitudes are related to the overall preparatory excitation level of a given cortical network, the more negative the more active—over the top of the scalp at electrode Cz (Birbaumer et al., 1999; Hinterberger et al., 2004). Attentional modulation seems to constitute the cognitive strategy in the physiological regulation of SCP. Birbaumer's team has widely shown that healthy subjects as well as severely paralyzed patients can learn to self-control their SCPs through operant conditioning; i.e., when they are provided with visual or auditory feedback of their SCPs and when SCP changes in the desired direction (positive or negative) are positively reinforced. As depicted in Figure 4, a trial typically consists of a 2-s preparatory phase in which the cursor remains stationary on the screen and an active feedback phase lasting between 2–8 s in which the cursor moves at constant speed from left to right, vertically controlled by the SCP amplitude. The onsets of these two phases are signaled by a high- and a low-pitched tone, respectively. For each trial, the user is required to produce either a negative or a positive SCP shift. The SCP amplitude shifts are referenced to the final SCP value of the 2-s preparatory phase immediately before the feedback starts. At the end of the feedback phase, the SCP shift is classified as a negative or positive response according to the integral of the SCP shift across the feedback period.

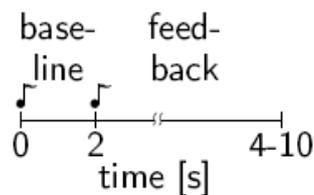


Figure 4: Experimental protocol used by Birbaumer's team to measure slow cortical potentials

Another possibility is to monitor slow premovement potentials such as the *Bereitschaftspotential (BP)*, or readiness potential (Blankertz et al., 2003; 2005). As shown in Figure 5, BP is a slow negative shift over the contralateral motor cortical area starting at 500-600 msec before the onset of the movement. As this is a slow potential, its dynamics is better observed if a low-pass filter—say, below 4 Hz—is applied before analysis of the EEG. Also, it is not necessary to use any baseline to compute it, what speeds up the decisions as it is not necessary to use long trials (as it is the case for SCP and synchronous protocols discussed in Section 0).

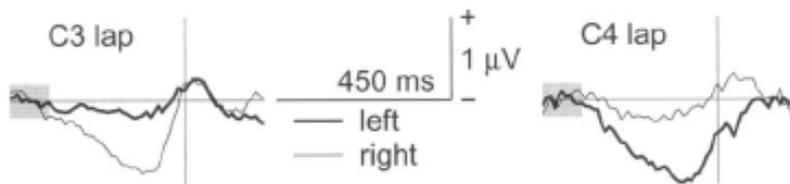


Figure 5: Grand averages of event-related movement potentials from self-paced left and right finger movements. Lateralization of the BP is clearly visible, a contralateral negatvation, for electrodes C3 and C4 over the motor cortex, left and right, respectively (reproduced from (Blankertz et al., 2003))

2.2.2 Rhythmic Activity

Apart from analyzing nonoscillatory event-related potentials in the temporal domain such as SCP and BP, other groups look at local variations of EEG rhythms in the frequency domain. Populations of neurons can form complex networks whereby feedback loops are responsible for the generation of oscillatory activity. In general, the frequency of such oscillations becomes slower with increasing number of synchronized neuronal assemblies (Singer, 1993). A particularly significant EEG rhythm can be recorded from the central region of the scalp overlying the sensorimotor cortex during the imagination of body movements (Babiloni et al., 2000; Birch et al., 2002; Blankertz et al., 2005; Pfurtscheller & Neuper, 1997; 2001; Wolpaw & McFarland, 2004; Wolpaw et al., 2000).

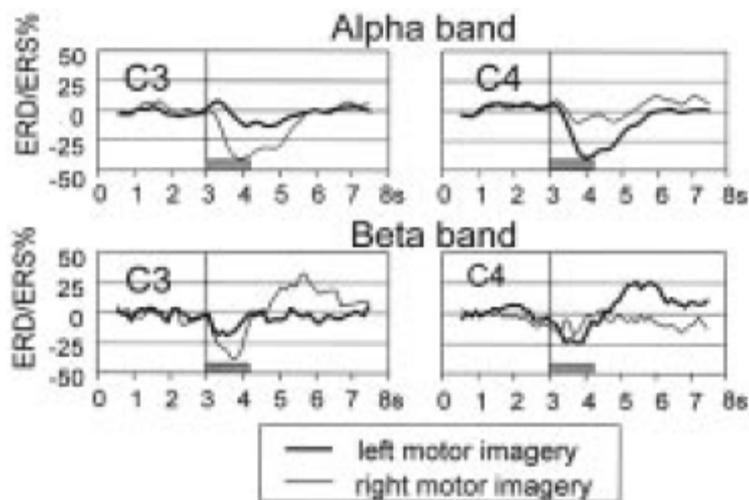


Figure 6: Grand average ERD/ERS curves recorded over left and right motor cortex (electrodes C3 and C4, respectively) during imagined hand movements. Positive and negative deflections, with respect to the reference baseline (see Figure 7), represent a band power increase (ERS) and decrease (ERD), respectively. The alpha band corresponds to the Rolandic μ rhythm (reproduced from (Pfurtscheller & Neuper, 2001))

In this respect, there exist two main paradigms. Pfurtscheller's team works with *event-related desynchronization (ERD)* (Pfurtscheller & Neuper, 2001). ERD is the basis of a number of BCIs (Babiloni et al., 2000; Blankertz et al., 2005). Imagination of hand movement gives rise to an amplitude

suppression—ERD—of Rolandic μ (8-12 Hz) and central β (13-28 Hz) rhythms over the contralateral primary hand motor cortical area (Pfurtscheller & Neuper, 1997). As shown in Figure 6 this imagination-related ERD shows different time courses in the two bands. In the μ band the ERD recovers to baseline level within a few seconds. On the other hand, the central β activity displays a short-lasting ERD followed by an amplitude increase—event-related synchronization (ERS).

In Pfurtscheller's approach, the ERD is computed at fixed time intervals after the subject is commanded to imagine specific movements of the limbs. Figure 7 illustrates the typical protocol (Pfurtscheller & Neuper, 2001). The experimental task is to imagine either right-hand or left-hand movement depending on a visually presented cue stimulus. The subject fixates on a computer monitor 150 cm in front of her/him. Each trial is 8 s long and starts with the presentation of a fixation cross at the center of the monitor, followed by a short warning tone (beep) at 2000 ms. At 3000 ms, the fixation cross is overlaid with an arrow at the center of the monitor for 1250 ms, pointing either to the left or to the right. Depending on the direction of the arrow, the subject is instructed to imagine, e.g., a movement of the left or the right hand. Recognition of the executed mental task is performed in a fixed time window from 3250 to 4250 ms. The sequence of "left" and "right" trials, as well as the duration of the breaks between consecutive trials (ranging between 500 and 2500 ms), is randomized throughout each experimental run. Finally, to compute the ERD/ERS, the EEG is first bandpass filtered and it is estimated the band power—using, for instance the Welch periodogram algorithm or an autoregressive model. Then, the power components are referred to the corresponding values of the band power of the reference baseline and transformed in dB—i.e., taking the logarithm of the division.

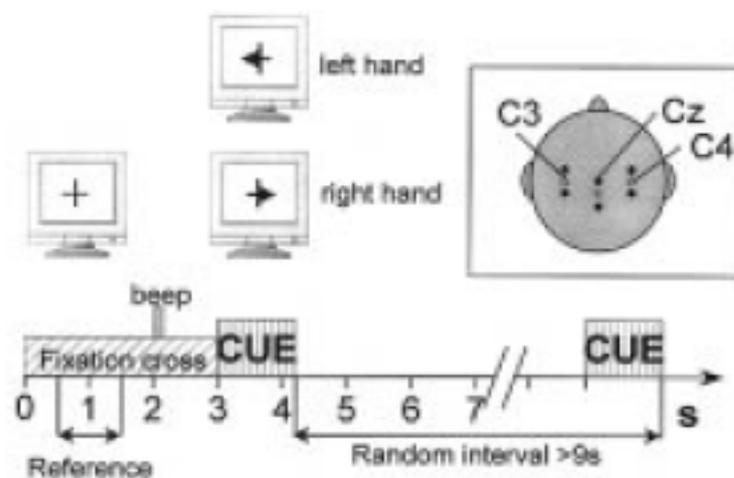


Figure 7: The cue stimulus in form of an arrow indicates the type of imagination. The reference period used as a baseline for calculation of ERD/ERS is indicated (reproduced from (Pfurtscheller & Neuper, 2001))

Alternatively, Wolpaw and coworkers analyze continuous changes in the amplitudes of the μ (8-12 Hz) or β (13-28 Hz) rhythms (Wolpaw & McFarland, 2004; Wolpaw et al., 2000). In this way, it is not necessary to

refer the band power amplitude to any baseline, thus speeding up the decision process. In Wolpaw's approach, people learn to control μ or β rhythm amplitude and use that amplitude to move a cursor in one or two dimensions to targets on a computer screen. A linear equation translates μ (or β) rhythm amplitude into a cursor movement. Figure 8 illustrates the control achieved by a well-trained user. In each trial, lasting several seconds, users move the cursor along a randomly selected direction and trials are interleaved with short resting periods (e.g., 1 s).

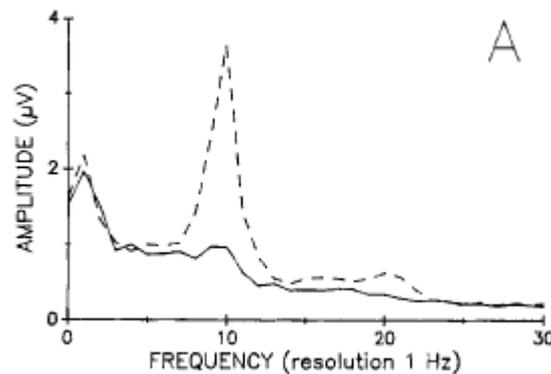


Figure 8: Frequency spectra of EEG recorded over sensorimotor cortex of a trained subject when the target is at the bottom (solid) or at the top (dashed) of the video screen. The main difference between the two spectra is in the 8–12 Hz rhythm band (and, to a lesser extent, in an 18–23 Hz rhythm band) (reproduced from (Wolpaw et al., 2000))

Finally, in addition to motor-related rhythms, some groups explore also other cognitive mental tasks (Anderson, 1997; Millán, 2003; Millán et al., 2004a, 2004b; Roberts & Penny, 2000). This approach is grounded in a number of neurocognitive studies that have found that different mental tasks—such as mental rotation of geometric figures (Yoshino et al., 2000), arithmetic operations (Chochon et al., 1999), or language (Petersen et al., 1988)—activate local cortical areas to a different extent. In particular, Millán's team analyzes also continuous variations of EEG rhythms, but not only on specific frequency bands. Their approach aims at discovering task-specific spatio-frequency patterns embedded in the continuous EEG signal—i.e., EEG rhythms over local cortical areas that differentiate the mental tasks.

2.3 Operant Conditioning & Machine Learning

Wolpaw et al. (2000) as well as Birbaumer et al. (1999) have demonstrated that some subjects can learn to control their brain activity through appropriate, but lengthy, training in order to generate fixed EEG patterns that the BCI transforms into external actions. In both cases the subject is trained over several months to modify the amplitude of either the SCP or μ/β rhythm, respectively. Other groups follow machine-learning approaches to train the classifier embedded in the BCI (Anderson, 1997; Blankertz et al., 2003; Millán et al., 2004a, 2004b; Pfurtscheller and Neuper, 2001; Roberts and Penny, 2000). Most of these approaches are based on a mutual learning process where the user and the brain interface are coupled together and adapt

to each other. This should accelerate the training time. Thus, Millán's approach allows subjects to achieve good performances in just a few hours of training in the presence of feedback (Millán, 2003; Millán et al., 2004a). In this case, analysis of learned EEG patterns confirms that for a subject to operate satisfactorily his/her personal BCI, the latter must fit the individual features of the former.

Most of these works deal with the recognition of just 2 mental tasks (Babiloni et al., 2000; Birbaumer et al., 1999; Birch et al., 2002; Blankertz et al., 2003; Pfurtscheller and Neuper, 2001; Roberts and Penny, 2000), or report classification errors bigger than 15% for 3 or more tasks (Kalcher et al., 1996; Anderson, 1997). An exception is Millán's approach that achieves error rates below 5% for 3 mental tasks, but correct recognition is 70% (Millán, 2003; Millán et al., 2004a). In the remaining cases (around 20-25%), the classifier doesn't respond, since it considers the EEG samples as uncertain. It is also worth noting that some of the subjects who follow Wolpaw's approach are able to control their μ/β rhythm amplitude at 4 different levels and/or have simultaneous control of two rhythms.

The incorporation of rejection criteria to avoid making risky decisions, such in the case of Millán's approach, is an important concern in BCI. From a practical point of view, a low classification error is a critical performance criterion for a BCI; otherwise users can become frustrated and stop utilizing the interface. The system of Roberts and Penny (2000) applies Bayesian techniques for rejection purposes too.

2.4 Synchronous vs. Asynchronous BCI

EEG-based BCIs are limited by a low channel capacity. Most of the current systems have a channel capacity below 0.5 bits/s (Wolpaw et al., 2002). One of the main reasons for such a low bandwidth is that they are based on *synchronous* protocols where EEG is time-locked to externally paced cues repeated every 4-10 s and the response of the BCI is the average decision over this period (Birbaumer et al., 1999; Obermaier, Müller and Pfurtscheller, 2001; Pfurtscheller & Neuper, 2001; Roberts & Penny, 2000; Wolpaw & McFarland, 2004; Wolpaw et al., 2000). Such synchronous protocols facilitate EEG analysis since the starting time of mental states are precisely known and differences with respect to background EEG activity can be amplified. Unfortunately, they are slow and BCI systems that use them normally recognize only 2 mental states, independently of the number of electrodes from which EEG is measured. In a synchronous experimental protocol, the subject must follow a fixed repetitive scheme to switch from a mental task to the next. A trial consists of two parts. A first cue warns the subject to get ready and, after a fixed period of several seconds, a second cue tells the subject to undertake the desired mental task for a predefined time. The EEG phenomena to be recognized are time-locked to the last cue and the BCI responds with the average decision over the second period of time.

On the contrary, other BCIs utilize more flexible *asynchronous* protocols where the subject makes self-paced decisions on when to stop doing a mental task and start immediately the next one (Birch et al., 2002; Millán, 2003; Millán et al., 2004a, 2004b; Roberts and Penny, 2000; Scherer et al.,

2004). In such asynchronous protocols the subject can voluntarily change the mental task being executed at any moment without waiting for external cues. The time of response of an asynchronous BCI can be below 1 second. For instance, in Millán's approach the system responds every 1/2 second. The rapid responses of asynchronous BCIs, together with their performance, give a theoretical channel capacity between 1 and 1.5 bits/s.

It is worth noting that the use of statistical rejection criteria, discussed in Section 2.3, also helps to deal with an important aspect of a BCI, namely "idle" states where the user is not involved in any particular mental task. In an asynchronous protocol, idle states appear during the operation of a brain-actuated device while the subject does not want the BCI to carry out any action. Although the classifier is not explicitly trained to recognize those idle states, the BCI can process them adequately by giving no response.

2.5 Spatial Filtering

EEG signals are characterized by a poor signal-to-noise ratio and spatial resolution. Their quality is greatly improved by means of a Surface Laplacian (SL) derivation, which requires a large number of electrodes (normally 64-128). The SL estimate yields new potentials that represent better the cortical activity originated in radial sources immediately below the electrodes. The superiority of SL-transformed signals over raw potentials for the operation of a BCI has been demonstrated in different studies (Babiloni et al., 2000; McFarland et al., 1997; Mouriño, 2003). SL filtering can be done either globally or locally. In the former case, the raw EEG potentials are first interpolated using spherical splines of order 2 and then it is taken the second spatial derivative which is sensitive to localized sources of electrical activity (Perrin et al., 1989, 1990). The second derivative is evaluated only at the locations of the desired electrodes. In the latter case, local method, the average activity of neighbouring electrodes—normally four—is subtracted from the electrode of interest. Normally, the SL is estimated with a high number of electrodes. But Babiloni et al. (2001) have shown that, for the operation of a BCI, global SL waveforms with either a low or a high number of electrodes give statistically similar classification results. Millán et al. (2004a, 2004b) compute SL derivations from a few electrodes using local methods. Mouriño et al. (2001) compare different ways to compute the SL based on a few electrodes.

Alternatively, raw EEG potentials can be transformed to the common average reference (CAR), which consists in removing the average activity over all the electrodes. Still another possibility is to use a data-driven approach to construct common spatial patterns (CSP), which finds spatial filters that are optimal for discrimination of two populations of EEG signals (Lemm et al., 2005; Müller-Gerking et al., 1999). CSP is based on the simultaneous diagonalization of two matrices—the variance matrices of the two populations—and finds directions—i.e., spatial filters—with the biggest difference in variance between the two classes. Contrarily to the other spatial filtering methods, a band-pass filter focusing on the rhythms of interest is applied to the EEG signals before the computation of CSP.

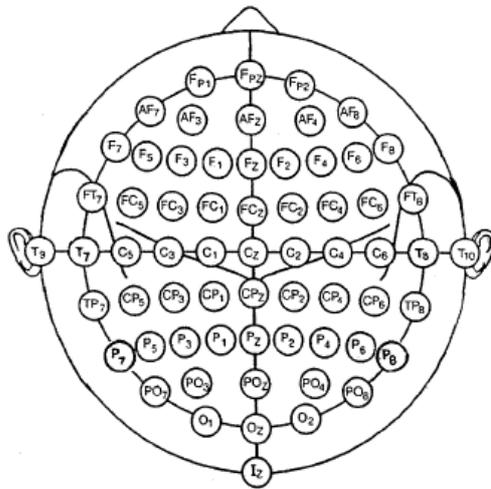


Figure 11: The standard placement of 64 scalp electrodes as an extension to the 10/20 international system

EEG signals are normally recorded with respect to an ear reference or with respect to a linked-ear reference (average potentials measured in both ear lobes). But the use of spatial filters (see Section 2.5) makes the transformed potentials reference-free.

4. Current Applications

BCI systems are being used to operate a number of brain-actuated applications that augment people's communication capabilities, provide new forms entertainment, and also enable the operation of physical devices. There exist virtual keyboards for selecting letters from a computer screen and write a message (Birbaumer et al., 1999; Farwell & Donchin, 1988; Millán, 2003; Millán et al., 2004a; Obermaier et al., 2003; Scherer et al., 2004; Wolpaw et al., 2000). Of these systems, the evoked BCI (Farwell & Donchin, 1988) has the highest performance. But, as mentioned previously, the need for external stimulation makes it less natural to use. Using the alternative spontaneous BCI systems, subjects can write a letter in times ranging from 22 seconds (Millán et al., 2004a) to 2 minutes (Birbaumer et al., 1999). In these approaches, the subject type letter by letter on the basis of binary or trinary choices. Initially, the whole keyboard is divided in two/three parts. Then, as the classifier embedded into the BCI recognizes the part the subject wants to select, the keyboard is successively split in smaller parts until a letter is selected. This letter goes to the message and the whole process starts over again. As an example, Figure 12 illustrates the operation of the virtual keyboard developed by Millán's lab.



Figure 12: Example of virtual keyboard. The figure shows a sequence of frames during the writing of a message (from left to right and top down). At the beginning, top left panel, the keyboard is divided in three parts, each associated to one of the mental tasks and using the same colors as during the training. Once the neural classifier recognizes the same mental task three times in a row, the corresponding part of the keyboard is selected (top center panel). In this case is the green area, which remains shadowed for 3.5 seconds to give the user the possibility to undo the selection in case it is wrong. Then, this part is divided again in three (top right panel). After a block of this second level is selected, it is still split in three to yield the choice among three letters (bottom left panel). The user then selects the letter with the red color (h) that is written into the message part and the whole process starts over again (bottom center panel). The bottom right panel shows the selection of the last letter in the message (reproduced from (Millán, 2003))

Millán (2003) illustrates the operation of a simple computer game, but other educational software could have been selected instead. Other “brain games” have been developed by Pfurtscheller’s team in Graz and Müller’s team in Berlin (personal communications). In Millán’s case, the “brain game” is the classical Pacman. For the control of Pacman, it suffices two mental tasks that make it turn left or right. Pacman changes direction of movement whenever one of the mental tasks is recognized twice in a row. In the absence of commands, Pacman moves forward until it reaches a wall, where it stops and waits for instructions (see Figure 13).



Figure 13: Example of “brain game”. Here the user controls the classical Pacman using only two commands to make it turn left or right. Otherwise, Pacman moves forward until it reaches a wall, where it stops (reproduced from (Millán, 2003))

On the other hand, it is also possible to make a brain-controlled hand orthosis open and close (Pfurtscheller & Neuper, 2001). Wolpaw and McFarland (2004) have recently demonstrated how subjects can learn to control two independent EEG rhythms and move a computer cursor in two dimensions. Despite these achievements, EEG-based BCIs are still considered too slow for controlling rapid and complex sequences of movements. But recently Millán and coworkers (2004a, 2004b) have shown for the first time that asynchronous analysis of EEG signals is sufficient for humans to continuously control a mobile robot—emulating a motorized wheelchair—along non-trivial trajectories requiring fast and frequent switches between mental tasks. Two human subjects learned to mentally drive the robot between rooms in a house-like environment visiting 3 or 4 rooms in the desired order (see Figure 14). Furthermore, mental control was only marginally worse than manual control on the same task. A key element of this brain-actuated robot is shared control between two intelligent agents—the human user and the robot—so that the user only gives high-level mental commands that the robot performs autonomously. In particular, the user’s mental states are associated with high-level commands (e.g., “turn right at the next occasion”) and that the robot executes these commands

autonomously using the readings of its on-board sensors. Another critical feature is that a subject can issue high-level commands at any moment. This is possible because the operation of the BCI is asynchronous and, unlike synchronous approaches, does not require waiting for external cues². The robot relies on a behaviour-based controller to implement the high-level commands to guarantee obstacle avoidance and smooth turns. In this kind of controller, on-board sensors are read constantly and determine the next action to take.

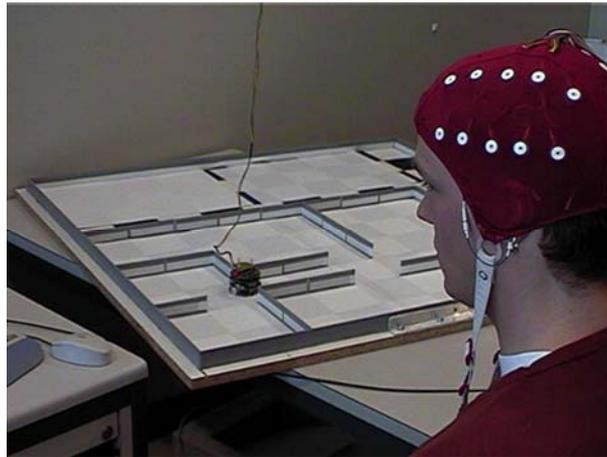


Figure 14: One of the users while driving mentally the robot through the different rooms of the environment, making it turn right, turn left, or move forward. The Khepera robot has 3 lights on top to provide feedback to the user and 8 infrared sensors around its diameter to detect obstacles (reproduced from (Millán et al., 2004a))

² As mentioned in Section 2.1, Rebsamen et al. (2006) have recently developed a wheelchair controlled with P300 evoked potentials. It should be noted that in this approach the user has only the possibility to choose the final destination from a short list of possible targets, what takes several seconds, and then the trajectory is generated in a fully automatic way.

5. Foreseen Improvements

Although these promising first results are attracting significant attention from an increasing number of research laboratories around the world, most of the issues being explored are related to “augmented communication” where fast decision-making is not critical as it is the case for real-time control of robotics devices and neuroprosthesis—i.e., control of prosthesis and orthosis directly from brain signals. Real-time control of brain-actuated devices, especially robots, is the most challenging for BCI and the most relevant for space applications.

While brain-actuated robots have been demonstrated in the laboratory, this technology is not yet ready to be taken out and used in real-world situations. A critical issue is how to improve the robustness of BCIs with the goal of making it a more practical and reliable technology. A first avenue of research is *online adaptation of the interface* to the user to keep the BCI constantly tuned to its owner (Buttfield et al., 2006; Millán, 2004; Millán et al., 2006). The point here is that, as subjects gain experience, they develop new capabilities and change their brain activity patterns. In addition, brain signals changes naturally over time. In particular, this is the case from a session (with which data the classifier is trained) to the next (where the classifier is applied). Thus, online learning can be used to adapt the classifier throughout its use and keep it tuned to drifts in the signals it is receiving in each session. Preliminary work shows the feasibility and benefits of this approach (Buttfield et al., 2006; Millán, 2004; Millán et al., 2006). In particular, a significant result is that online adaptation makes it possible to complete the task of driving a wheelchair along a corridor while avoiding obstacles from the very first trial.

The second line is the *analysis of neural correlates of high-level cognitive and affective states* such as errors, alarms, attention, frustration, confusion, etc. Information about these states is embedded in the EEG together with the mental commands intentionally generated by the user. The ability to detect and adapt to these states would enable the BCI to interact with the user in a much more meaningful way. One of these high-level states is the awareness of erroneous responses, whose neural correlate arises in the millisecond range. Thus, user’s commands are executed only if no error is detected in this short time. Recent results have shown satisfactory single-trial recognition of errors that leads to significant improvement of the BCI performance (Ferrez & Millán, 2005, 2006). In addition, this new type of error potential—which is generated in response to errors made by the BCI rather than by the user—may provide with performance feedback that, in combination with online adaptation, could allow us to improve the BCI while it is being used.

A third issue is how to get a better picture of electrical activity all across the brain with high spatial accuracy without implanting electrodes but rather by a non-invasive estimation from scalp EEG signals. Local field potentials (LFP) are produced by the electrical activity of small groups of neurons. LFP have proven to be as efficient in predicting animal’s behaviour or cognitive

states as the information carried by the spike rate of individual neurons (Mehring et al. 2003; Pesaran et al., 2002). Recent developments in electrical neuroimaging allow the transformation of scalp recorded EEG into *estimated local field potentials (eLFP)* as if they were directly recorded within the brain (Grave de Peralta et al., 2004). Non-invasive eLFP has the potential to unravel scalp EEG signals, attributing to each brain area its own temporal (spectral) activity. Preliminary results have shown significant improvements in the classification of bimanual motor tasks using eLFP with respect to scalp EEG (Grave de Peralta et al., 2005, 2006). Also, for a couple of patients where it was also possible to record intracranial potentials directly, eLFP and intracranial potentials had similar predicting power (Grave de Peralta et al., 2006). Finally, it is also worth noting that through this technique we can also gain a better understanding of the nature of the brain activity driving the BCI.

Still a fourth issue is the *nature and role of feedback* for brain-actuated control. In particular, an open question is the use of multiple modalities of feedback (visual, auditory, haptic and vestibular) to accelerate user training and facilitate accurate control of the robots. The rationale behind is that it is well known that disabled people (and healthy people too) learn better manipulation skills (among others) if they are provided with multiple sources of feedback, in particular haptic. An additional benefit of the use of the haptic feedback is to free visual and auditory attention to follow the process the user is controlling. This fact could open the way for a larger use of such brain-actuated devices able to preserve the visual and auditory processes that are usually engaged in the normal brain surveillance activity. In this way, we hope users will get a more precise feeling of the capabilities of the robot in undertaking a task as well as on what the robot is doing what will facilitate both the acquisition of better mental commands and conveying faster corrective mental commands in case of undesired actions by the robot. Initial unpublished results seem to indicate that haptic feedback is as effective as standard visual feedback for user training.

Finally, a limiting factor of current EEG-based BCI is the recording technology that requires the use of gel to improve the conductivity of the electrical signals generated in the brain. This is a cumbersome procedure as a proper amount of gel has to be smeared in each electrode. However, recent advances in so-called *dry* electrodes, which only require a good contact with the scalp to record brain signals, promise to change the situation in the coming years and enable the easy use of a large number of electrodes directly integrated in a helmet.

6. BCI for Space Applications

As mentioned before, development of non-invasive brain-controlled robotic devices is the most relevant for space applications, where environment is inherently hostile and dangerous for astronauts who could greatly benefit from direct mental teleoperation of external semi-automatic manipulators. Such a kind a brain-actuated control should increase the efficiency of astronaut's activity that is of primary interest as mental commands could be sent without any output delays—as it is the case for manual control in microgravity conditions. Furthermore, robotics aids would be highly useful to astronauts weakened by long stays in microgravity environments.

In this respect, there is a need to incorporate shared autonomy principles into the BCI. In shared control, the intelligent controller relieves the human from low level tasks without sacrificing the cognitive superiority and adaptability of human beings that are capable of acting in unforeseen situations. In other words, in shared control there are two intelligent agents—the human user and the robot—so that the user only conveys intents that the robot performs autonomously (Sheridan, 1992). Although the Millán's brain-actuated robot had already some form of cooperative control, shared autonomy is a more principled and flexible framework.

But, EEG signals in a microgravity environment may differ from those recorded in a normal gravity environment for the same person. As a result, the feasibility of BCI for space applications should be tested in microgravity conditions and, depending on the results, new solutions should be explored that fit better space environments. Examples of those possible alternatives for space BCI are specific tasks or cognitive functions that do not suffer from microgravity effects, such as vertigo and spatial disorientation, and rhythms that subjects can sustain better.

7. Future Technologies and Roadmaps for BCI

BCI is a field still in its infancy, whose bit-rate is still far away from other interaction modalities such as speech or body movements (e.g., eye tracking, gestures). But, as discussed in Section 1, recent experiments with monkeys having implanted electrodes in their brain support the feasibility of controlling in real time complex devices such as a prosthetic limb directly by brain activity. However, given the invasive nature of this approach, the challenge is to achieve similar results with non-invasive technologies.

For this we will need to use portable high-resolution EEG systems (possibly in combination with near-infrared spectroscopy, NIRS, that yield complementary information and it is also portable) to get detailed information on the activity of small cortical areas. It will be then crucial to develop real-time algorithms to transform scalp potentials into brain activity maps, such as estimated local field potentials (Section 5) and select relevant areas of interest for the recognition task. The neural classifier embedded in the BCI would work upon these brain maps instead of using EEG features.

Although the immediate application of BCI is to help physically impaired people, its potentials are extensive. Ultimately they may lead to the development of truly adaptive interactive systems that, on the one side, augment human capabilities by giving the brain the possibility to develop new skills and, on the other side, make computer systems fit the pace and individual features of their owners. Most probably, people will use BCI in combination with other sensory interaction modalities (e.g., speech, gestures) and physiological signals (e.g., electromyogram, skin conductivity). Such a multimodal interface will yield a higher bit rate of communication with better reliability than if only brainwaves were utilized. But, in order to do so, it is first necessary to improve the performance of BMIs until they reach similar levels to other modalities. On the other hand, the incorporation of other interaction modalities highlights a critical issue in BCI, namely the importance of filtering out from the recorded brain signals non-CNS artifacts originated by movements of different parts of the body. *Independent component analysis (ICA)* is a method for detecting and removing such artefacts (Vigário, 1997).

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