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Brain-Computer Interfaces

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Introduction

There is a growing interest in the use of physiological signals for communication and operation of devices for the severely motor disabled as well as for able-bodied people. Over the last decade evidence has accumulated to show the possibility to analyze brainwaves on-line to derive information about the subjects' mental state that is then mapped into some external action such as selecting a letter from a virtual keyboard or moving a robotics device. A *brain-computer interface (BCI)* is an alternative communication and control channel that does not depend on the brain's normal output pathway of peripheral nerves and muscles (Wolpaw et al., 2000).

Most BCI systems use electroencephalogram signals (see EEG ANALYSIS) measured from scalp electrodes that do not require invasive procedures. Although scalp EEG is a simple way to record brainwaves, it does not provide detailed information on the activity of single neurons (or small clusters of neurons) that could be recorded by implanted electrodes in the cortex (see PROSTHETICS, NEURAL). Such a direct measurement of brain activity may, in principle, enable faster recognition of mental states and even achieving more complex interactions.

A BCI may monitor a variety of brainwave phenomena. Some groups exploit evoked potentials generated in response to external stimuli (see Wolpaw et al., 2000 for a review). Evoked potentials are, in principle, easy to pick up but constrain the subject to get synchronized to the external machinery. A more natural and practical alternative is to rely upon components associated with spontaneous mental activity. Such spontaneous components range from slow cortical potentials of the EEG (e.g., Birbaumer et al., 1999), to variations of EEG rhythms (e.g., Wolpaw and McFarland, 1994; Kalcher et al., 1996; Anderson, 1997; Roberts and Penny, 2000; Millán et al., 2002b), to the direct activity of neurons in the cortex (e.g., Kennedy et al., 2000; Wessberg et al., 2000).

Direct Brain-Computer Interfaces

Direct BCIs involve invasive procedures to implant electrodes in the brain (see PROSTHETICS, NEURAL). Apart from ethical concerns, a major difficulty is to obtain reliable long-term recordings of neural activity. Recent advances have made possible to develop direct BCIs with animals and even human beings.

Kennedy and colleagues (2000) have implanted a special electrode into the motor cortex of several paralyzed patients. These electrodes contain a neurotrophic factor that induces growth of neural tissue within the hollow electrode tip. With training, patients learn to control the firing rates of the multiple recorded neurons to some extent. One of them is able to drive a cursor and write messages.

Wessberg et al. (2000) have recorded the activity of ensembles of neurons with microwire arrays implanted in multiple cortical regions involved in motor control, as monkeys performed arm movements. From these signals they have obtained accurate real-time predictions of arm trajectories and have been able to reproduce the trajectories with a robot arm. Although these experiments do not describe an actual BCI, they support the feasibility of controlling complex prosthetic limbs directly by brain activity. In addition, earlier work by Nicolelis and colleagues showed that neural predictors can be derived for rats implanted with the same kind of microelectrodes (see Nicolelis, 2001 for details and reference). The rats were trained to press a bar to move a simple device delivering water and, later, learned to operate this device through neural activity only.

For a more detailed analysis and prospects of this area, see Nicolelis (2001).

Non-Invasive Brain-Computer Interfaces

Non-invasive BCIs are based on the analysis of EEG phenomena associated with various aspects of brain function. Thus, Birbaumer et al. (1999) measure slow cortical potentials (SCP) over the vertex (top of the scalp). SCP are shifts in the depolarization level of the upper cortical dendrites and indicate the overall preparatory excitation level of a cortical network. Other groups look at local variations of EEG rhythms. The most used of such rhythms are related to the imagination of movements and are recorded from the central region of the scalp overlying the sensorimotor cortex. In this respect, there exist two main paradigms. Pfurtscheller's team works with event-related desynchronization (ERD, see EEG ANALYSIS) computed at fixed time intervals after the subject is commanded to imagine specific movements of the limbs (Kalcher et al., 1996; Obermaier, Müller and Pfurtscheller, 2001). Alternatively, Wolpaw and coworkers analyze continuous changes in the amplitudes of the μ (8-12 Hz) or β (13-28 Hz) rhythms (Wolpaw and McFarland, 1994). Finally, in addition to motor-related rhythms, Anderson (1997) and Millán et al. (2002b) also analyze continuous variations of EEG rhythms, but not only over the sensorimotor cortex and in specific frequency bands. The reason is that a number of neurocognitive studies have found that different mental tasks—such as imagination of movements, arithmetic operations, or language—activate local cortical areas at different extents. The insights gathered from these studies guide the placement of electrodes to get more relevant signals for the different tasks to be recognized. In this latter case, rather than looking for predefined EEG phenomena as in the previous paradigms, the approach aims at discovering EEG patterns embedded in the continuous EEG signal associated with different mental states.

Most of the existing BCIs are based on synchronous experimental protocols where the subject must follow a fixed repetitive scheme to switch from a mental task to the next (Wolpaw and McFarland, 1994; Kalcher et al., 1996; Wolpaw and McFarland, 1994; Birbaumer et al., 1999; Obermaier, Müller and Pfurtscheller, 2001). 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. In these synchronous BCI systems, the shortest trial lengths that have been reported are 4 s (Birbaumer et al., 1999) and 5 s (Obermaier, Müller and Pfurtscheller, 2001). This relatively long time is necessary because the EEG phenomena of interest, either SCP or ERD, need some seconds to recover. On the contrary, other BCIs rely upon 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 (Roberts and Penny, 2000; Millán et al., 2002b). In this second case, the time of response of the BCI goes from 0.5 s (Millán et al., 2002b) to several seconds (Roberts and Penny, 2000).

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 (for details see McFarland et al., 1997; Babiloni et al., 2001; and references therein). The superiority of SL-transformed signals over raw potentials for the operation of a BCI has been demonstrated in different studies (e.g., McFarland et al., 1997). While significant progress has been obtained (and will still continue) with studies using a high number of EEG electrodes (from 26 to 128), today's practical BCI systems should have a few electrodes (no more than 10) to allow their operation by laypersons, as the procedure of electrode positioning is time consuming and critical. Most groups have developed BCI prototypes with a limited number of electrodes that, however, do not benefit from SL transformations. On the contrary, Babiloni et al. (2001) and Millán et al. (2002b) compute SL derivations from a few electrodes, using global and local methods respectively.

Wolpaw and McFarland (1994) 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 rhythm, respectively. A few other groups follow machine learning approaches to train the classifier embedded in the BCI. These techniques range from linear classifiers (Babiloni et al., 2001; Obermaier, Müller and Pfurtscheller, 2001), to compact multi-layer perceptrons and Bayesian neural networks (Anderson, 1997; Roberts and Penny, 2000), to variations of LVQ (Kalcher et al., 1996), to local neural classifiers (Millán, 2002; Millán et al., 2002b). Most of these works deal with the recognition of just 2 mental tasks (Roberts and Penny, 2000; Babiloni et al., 2001; Obermaier, Müller and Pfurtscheller, 2001), 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, 2002; Millán et al., 2002b). Obermaier, Müller and Pfurtscheller (2001) reports on a single disabled person who, after several months of training, has reached a performance level close to 100%. It is also worth noting that some of the subjects who follow Wolpaw's approach are able to control their μ rhythm amplitude at 4 different levels. These classification rates, together with the number of recognizable tasks and duration of the trials, yield bit rates from approximately 0.15 to 2.0.

Some approaches are based on a mutual learning process where the user and the brain interface are coupled together and adapt to each other (Roberts and Penny, 2000; Obermaier, Müller and Pfurtscheller, 2001; Millán, 2002; Millán et al., 2002b). This should accelerate the training time. Thus, Millán's approach has allowed subjects to achieve good performances in just a few hours of training (Millán, 2002; Millán et al., 2002b). 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 (Millán et al., 2002a).

Another important concern in BCI is the incorporation of rejection criteria to avoid making risky decisions for uncertain samples. This is extremely important from a practical point of view. Roberts and Penny (2000) apply Bayesian techniques for this purpose, while Millán et al. (2002b) use a confidence probability threshold. In this latter case, more than 10 subjects have experimented with their BCI (Millán, 2002; Millán et al., 2002b). Most of them were trained for a few consecutive days (from 3 to 5). Training time was moderate, around 1/2 hour daily. Experimental results show that, at the end of training, the correct recognition rates are 70% (or higher) for three mental tasks. This figure is more than twice random classification. This modest rate is largely compensated by two properties: wrong responses are below 5% (in many cases even below 2%) and decisions are made every 1/2 second. Some other subjects have undertaken consecutive training sessions (from 4 to 7) in a single day. None of these subjects had previous experience with BCIs and, in less than 2 hours, all of them reach the same excellent performance as above. It is worth noting that one of the subjects is a physically impaired person suffering from spinal muscular atrophy.

Brain-Actuated Applications

These different BCI systems are being used to operate a number of brain-actuated applications that augment people's communication capabilities, provide new forms of education and 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; Obermaier, Müller and Pfurtscheller, 2001; Millán, 2002). Using these three different approaches, subjects can write a letter every 2 minutes, 1 minute and 22 seconds, respectively. Wolpaw's group has also its own virtual keyboard (Wolpaw, personal communication). A patient who has been implanted Kennedy and colleagues' special electrode has achieved a spelling rate of about 3 letters per minute using a combination of neural and EMG signals (Kennedy et al., 2000).

On the other hand, it is also possible to make a brain-controlled hand orthosis open and close (see references in Wolpaw et al., 2000; Obermaier, Müller and Pfurtscheller, 2001) and even guide in a continuous manner a motorized wheelchair with on-board sensory capabilities (Millán, 2002). In this latter case, the key idea is that user's mental states are associated with high-level commands that the wheelchair executes autonomously (see ROBOT NAVIGATION). Another critical aspect for the control of the wheelchair is that subjects can issue high-level commands at any moment as the operation of the BCI is self-paced and does not require waiting for specific events.

Finally, Millán (2002) illustrates the operation of a simple computer game, but other educational software could have been selected instead.

Discussion

Despite recent advancements, BCI is a field still in its infancy and several issues need to be addressed to improve the speed and performance of BCI. One of them is the exploration of local components of brain activity with fast dynamics that subjects can consciously control. For this we will need increasing knowledge of the brain (where and how cognitive and motor decisions are made) as well as the application of more powerful digital signal processing (DSP) methods than those commonly used to date. In addition, extraction of more relevant features, by means of these DSP methods, together with the use of more appropriate classifiers will improve BCI performance in terms of classification rates and number of recognizable mental tasks. A possibility is to apply recurrent neural networks to exploit temporal dynamics of brain activity. However, a main limitation for scaling up the number of recognizable mental tasks is the quality—signal-to-noise ratio (SNR) and resolution—of the measured brain signals. This is especially true in the case of EEG-based BCIs, where the SNR is very poor and we cannot get detailed information on the activity of small cortical areas unless we use a large number of electrodes (64, 128 or more). It is then crucial to develop better electrodes that are also easy to position, thus enabling the use of a large number of them even by laypersons. Finally, another key concern is to keep the BCI constantly tuned to its owner. This requirement arises because, as subjects gain experience, they develop new capabilities and change their EEG patterns. In addition, brain activity changes from a session (with which data the classifier is trained) to the next (where the classifier is applied). The challenge here is to adapt on-line the classifier while the subject operates a brain-actuated application, even if the subject's intention is not known until later. In this respect, local neural networks are better suited for ON-LINE LEARNING (q.v.) than other methods due to their robustness against catastrophic interference. This list of topics is non exhaustive, but space limits prevent further discussion (see Wolpaw et al., 2000 for additional details on these and other issues).

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. 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 (q.v.) is a method for detecting and removing such artifacts.

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