# 60. EEG-Based Brain-Computer Interfaces

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## Introduction and Basic Principles

A relatively recent development in applied neurophysiology is an approach called electroencephalogram (EEG)-based brain-computer interfaces (BCIs), by means of which specific features automatically extracted from EEG signals are used to operate computer-controlled devices to assist patients who have highly compromised motor functions, as is the case of tetraplegic patients. This novel approach became possible due to advances both in methods of EEG analysis and in information technology, allied to a better understanding of the psychophysiological correlates of certain EEG features. Therefore, it is interesting to take notice of the emerging field of BCI, which is a technical system that allows direct communication between brain and computer (Vidal, 1973). BCI provides a communication channel that can be used to convey messages and commands directly from the brain to the external world. For this purpose, the processing of brain signals [EEG, electrocorticogram (ECoG), multiunit activity] has to be done in real time.

The current, most important applications of a BCI include the restoration of communication for patients in a locked-in state and the control of neuroprosthesis in patients with spinal cord injuries (Pfurtscheller and Neuper, 2001; Wolpaw et al., 2002). In addition to these applications, we should also note the field of neurofeedback therapy and the upcoming field of multimedia and virtual reality applications (Ebrahimi et al., 2003).

A BCI system, in general, contains components for feature extraction and classification (detection) of EEG events (Fig. 60.1). The goal of the feature extraction component is to find a suitable representation of the EEG signal that simplifies the subsequent classification or detection of specific patterns of electrical brain activity. That is, the signal features should encode the commands sent by the user, but should not contain noise and other signal components that can impede the classification process. There are various feature extraction methods used in current BCI systems. A nonexhaustive list of these methods includes amplitude and band power measures, Hjorth parameters, autoregressive parameters, and wavelet coefficients (Graimann et al., 2003; Obermaier et al., 2001; Pfurtscheller and Neuper, 2001).

The task of the classifier is to use the signal features provided by the feature extractor to assign the recorded samples of the signal to a given category of EEG patterns. In the simplest form, detection of an EEG pattern may be made, for instance, by means of a threshold method (Birbaumer et al., 2000; Levine et al., 2000). More sophisticated classification algorithms of different EEG patterns depend on the use of linear or nonlinear classifiers (Blankertz et al., 2002; Millan et al., 2002; Pfurtscheller and Neuper, 2001).

The classifier output, which can be a simple on-off signal or a signal that encodes a number of different classes, is transformed into an appropriate signal that can then be used to control a variety of devices. For most current BCI systems, the output device is a computer screen, and the desired output consists of the selection of certain targets. Advanced applications include controlling of spelling systems or other external apparatuses such as prosthetic devices and multimedia applications.

Feedback of performance is usually obtained by visualization of the classifier output on a computer screen or by presentation of an auditory, tactile, or visual feedback signal. Feedback is an integral part of the BCI system because the users have to receive information about the behavior of the devices that they controlled, by means of the brain signals they produced.

When the user performs a mental task and, therewith, intends to transmit a message, the BCI enters into operation. In principle, two distinct modes of operation can be distinguished, the first being externally paced (cue-based, computer-driven, synchronous BCI) and the second internally paced (non-cue-based, user-driven, asynchronous BCI). In the case of a synchronous BCI, a fixed, predefined time window is used. After a visual or auditory cue stimulus, the subject has to act and produce a specific brain pattern. Nearly all known BCI systems work in such a cue-based mode (Kübler et al., 2001; Pfurtscheller and Neuper, 2001; Wolpaw et al., 2002). An asynchronous protocol requires a continuous analysis and feature extraction of the recorded brain signal. Thus, such BCIs are in general, even more demanding and more complex than BCIs operating with a fixed timing scheme. To date, only a few research groups have been working on asynchronous BCI systems (Blankertz et al., 2002; Graimann et al., 2003; Levine et al., 2000; Mason and Birch, 2000).

## EEG Patterns Used As Input for a BCI

In the EEG (as well as in the ECoG) two types of phenomena can be differentiated that are relevant for a BCI system:

1. Event-related potentials (ERPs), including evoked potentials, slow cortical potential (SCP) shifts, and steady-state evoked potentials.
2. Event-related changes of ongoing EEG activity in specific frequency bands. Event-related desynchronization (ERD) defines an amplitude (power) decrease of a rhythmic component, whereas event-related synchronization (ERS) characterizes an amplitude (power) increase (Pfurtscheller and Lopes da Silva, 1999; see also Chapter 51).

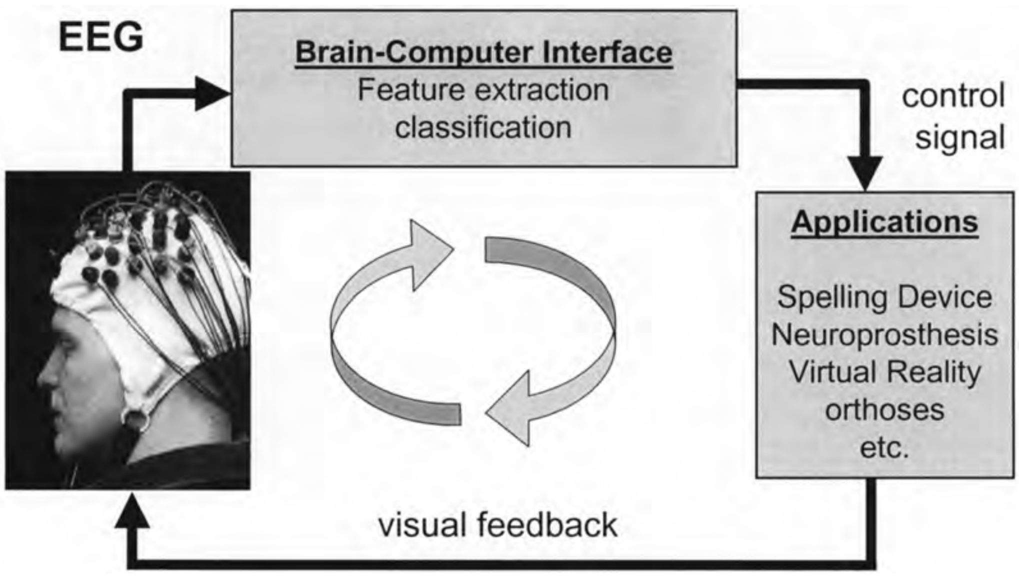


**Figure 60.1.** Basic principle of an EEG-based brain–computer interface (BCI) system. EEG signals from the user's brain are acquired and processed to extract specific features used for classification. The classifier output is transformed into a device command to operate the respective application, which, at the same time, provides feedback to the user.

In a simplified form it may be assumed that ERPs represent the summative responses of cortical neurons due to changes of the afferent activity, while ERD/ERS reflect changes of the activity of local interactions between main neurons and interneurons that control the frequency components of ongoing EEG/ECoG components.

Slow cortical potentials (SCPs) are slow shifts of the EEG with a duration from 300 ms to several seconds. These signals have been used by Birbaumer et al. (1999) to operate the so-called EEG-based thought–translation device, in which the subjects learn to produce negative or positive SCP shifts by means of biofeedback.

A communication system that made use of the P300 component of visual evoked potentials (VEPs) was developed by Donchin et al. (2000). This BCI is based on the presentation of a 6 × 6 letter matrix in which rows and columns are flashed at short intervals. When the user's attention focuses on a certain item, a large P300 amplitude is produced.

BCI systems based on the evaluation of steady-state visual evoked potentials (SSVEPs) were reported by Middendorf et al. (2000) and Cheng et al. (2003). The system of Cheng et al. uses 13 buttons arranged as a virtual telephone keypad and flickering at different frequencies. The subject has to direct his/her gaze to one of the flashing buttons in order to enhance the amplitude of the corresponding flicker frequency (SSVEP).

With the BCI system of Wolpaw et al. (2000, 2002) subjects with motor disabilities learn to control the amplitude of mu and beta rhythms and use these control signals to move a cursor, in one or two dimensions, to targets on a computer screen. In a similar way, the Graz-BCI system transforms the dynamics of mu and central beta rhythms (ERD, ERS) during motor imagery into a control signal that can be used to operate a virtual keyboard (Neuper et al., 2003; Obermaier et al., 2001), or to control the operation of a prosthetic device to restore hand grasp function (Pfurtscheller et al., 2000, 2003b) (for more details, see Applications, below).

## Motor Imagery As Control Strategy

Several EEG studies indicate that primary sensorimotor areas are activated when subjects imagine the execution of a hand movement. Klass and Bickford (1957) and Chatrian et al. (1959) observed blocking or desynchronization of the central mu-rhythm with motor imagery. By means of quantification of the temporal-spatial ERD pattern, it was clearly shown that one-sided hand motor imagery can result in a lateralized activation of sensorimotor areas, similarly to that found in the preparatory phase of a self-paced hand/finger movement (Pfurtscheller and Neuper, 1997). Furthermore, measurements of slow potential shifts (Beisteiner et al., 1995) have shown that similar changes over the contralateral hand area can be observed during execution and imagination of movement. Also multichannel neuromagnetic measurements demonstrated the effect of motor imagery on brain oscillations generated in primary motor areas (Schnitzler et al., 1997).

An example is shown in Fig. 60.2 in the form of band power time courses of 11- to 13-Hz EEG activity. The ERD/ERS curves show different reactivity patterns during right and left motor imagery, displaying a significant band power decrease (ERD) over the contralateral hand area. It is of interest to note, first, that contralateral to the side of motor imagery an ERD and ipsilaterally an ERS were present and, second, that feedback enhanced the difference between both patterns and therewith the classification accuracy (see also Neuper et al., 1999).

The enhancement of oscillatory EEG activity (ERS) during motor imagery is a very important aspect in BCI

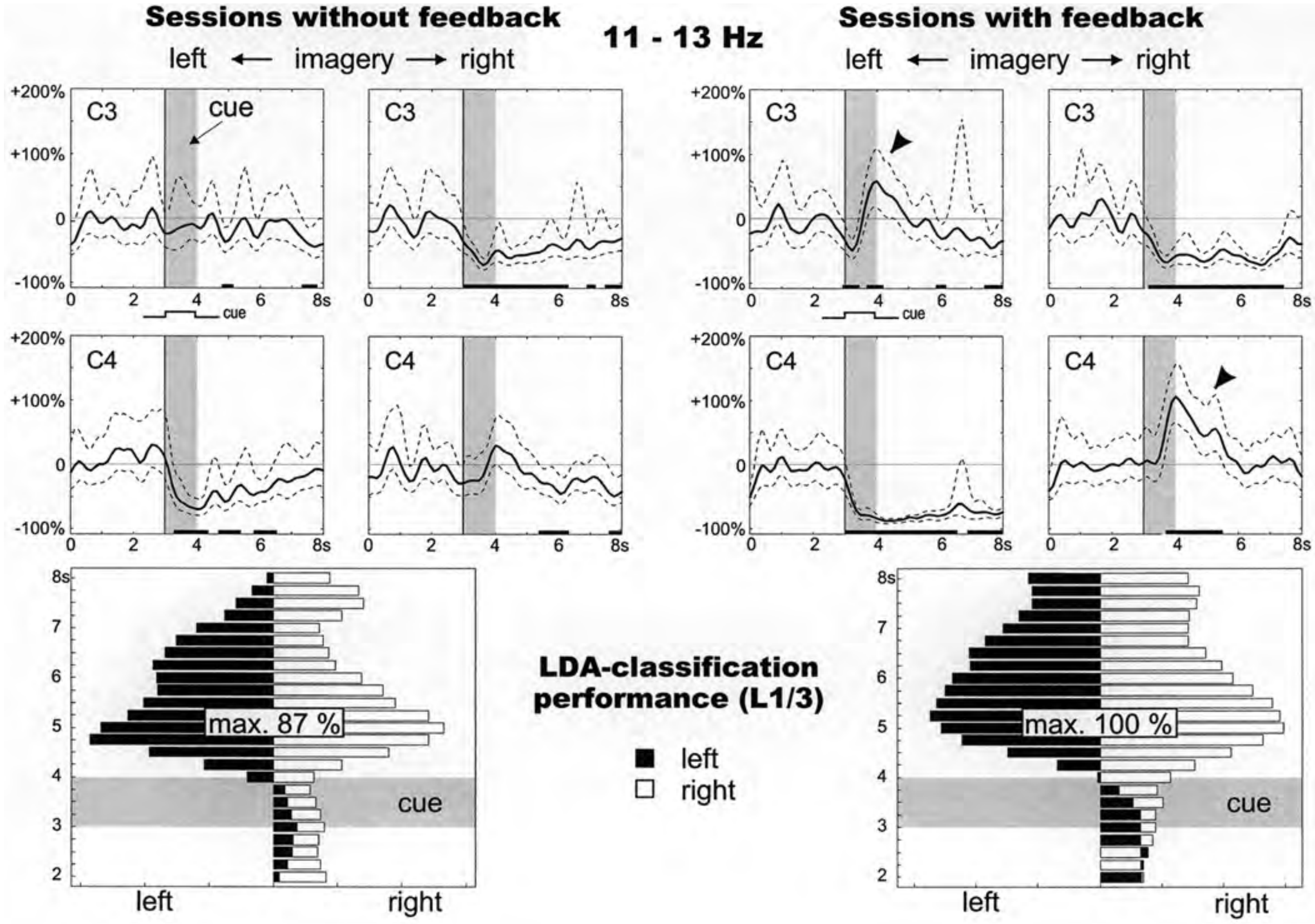


**Figure 60.2.** **Top:** Event-related desynchronization (ERD)/event-related synchronization (ERS) curves (11–13 Hz; 95% confidence intervals indicated) of one representative subject during imagined movements of the left versus right hand, in sessions without feedback **(left panels)** and in sessions with continuously present feedback **(right panels).** Data were recorded from the sensorimotor cortex (C3, C4). The time period of cue presentation is indicated by a *gray vertical bar.* **Bottom:** Examples of classification results of single trials (based on linear discriminant analysis, LDA) of two selected sessions, one without **(left side)** and one with feedback **(right side),** respectively. The x-axis denotes the average size of the distance function (resulting from LDA) for all left and right trials of one session (for details, see Neuper et al., 1999). In the session with feedback, the average distance corresponds to the average length of the feedback bar presented on the screen. *Black bars* indicate bar movements to the left side of the screen, *white bars* indicate bar movements to the right side. The y-axis displays the time points used for classification. The best classification accuracy for each session is indicated.

research. For example, foot motor imagery can induce beta oscillations over the foot representation area close to the vertex (Fig. 60.3), but also mu oscillations over both hand representation areas (Neuper and Pfurtscheller, 1999).

Summarizing, it can be stated that motor imagery can modify sensorimotor rhythms in a similar way to that observed in the preparatory phase of an executed movement. Since motor imagery results in somatotopically organized activation patterns, mental imagination of different movements (e.g., left vs. right hand; hand vs. foot) can be an efficient strategy to operate a BCI based on oscillatory EEG activity. The challenge is to detect the imagery-related changes in ongoing, unaveraged EEG recordings.

## Training Paradigm and Information Transfer Rate

The use of the P300 component (Donchin et al., 2000) or the SSVEP (Cheng et al., 2002) for communication requires some conscious control of eye muscles and therefore is not applicable for some categories of patients, e.g., in the late stages of amyotrophic lateral sclerosis (ALS). In these cases EEG-based control by means of a motor imagery strategy may be the only way to establish a communication channel. A very important step in EEG-based communication with motor imagery is that the computer has to learn to recognize EEG patterns associated with one or more states of mental imagery. This implies that the computer has to be adapted to

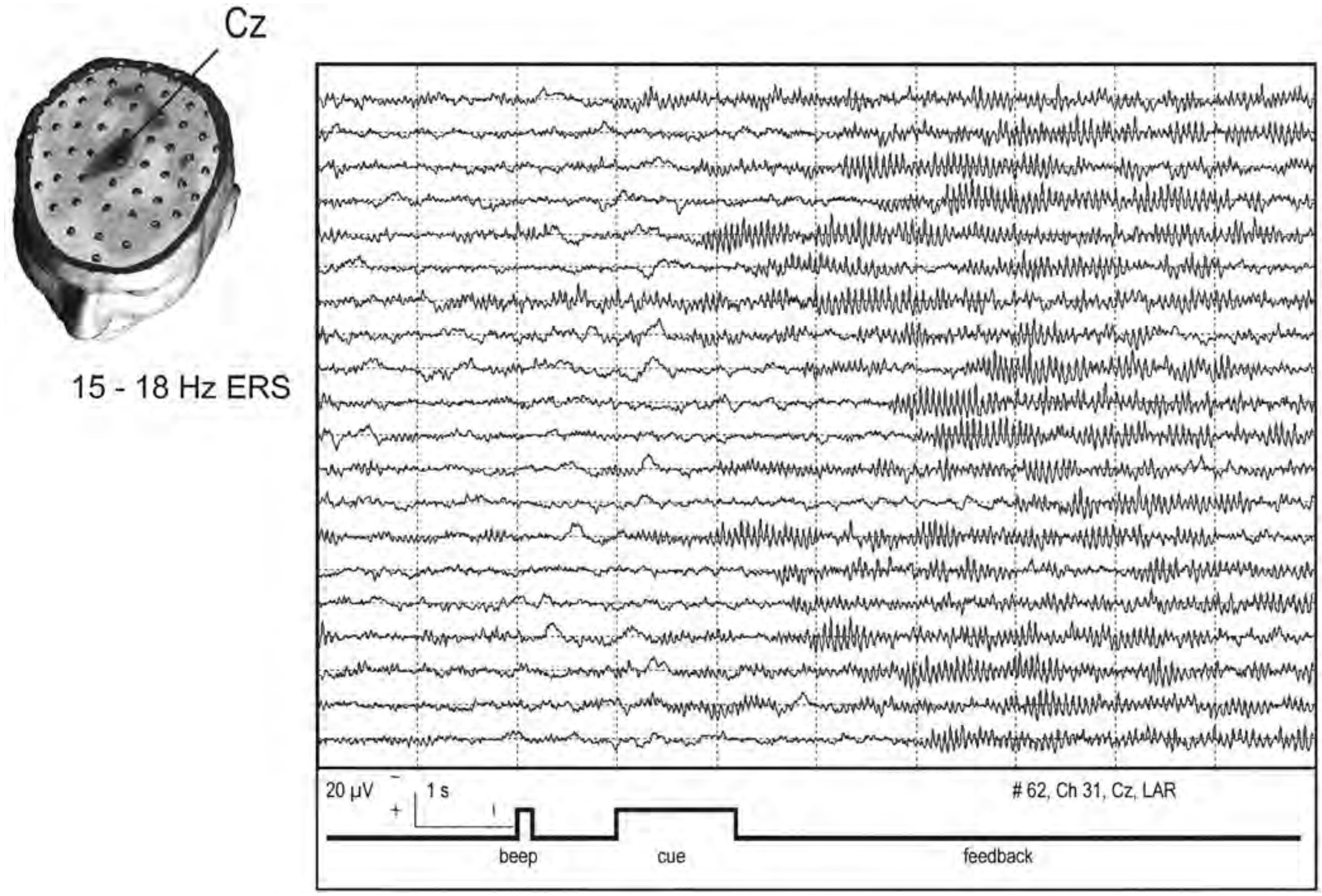


**Figure 60.3.** **Right side:** Examples of single EEG trials (tetraplegic patient T.S.) during foot motor imagery showing trains of 17-Hz beta oscillations. **Left side:** Topographic map indicating the localized 17-Hz ERS close to the electrode position Cz.

the brain activity of a specific subject, a process that can last for many days or weeks. After a learning or training process, and when a classifier is available, the online classification of single EEG trials can start, and feedback can be provided. To keep the training period as short as possible, an efficient training strategy is necessary. One example of this is the so-called basket game, in which the user has to mentally move a falling ball into the correct goal ("basket") marked on the screen (Fig. 60.4, left side) (Krausz et al., 2003). The horizontal position of the ball is controlled via the BCI output signal and the falling speed can be adjusted by the investigator. Four male volunteers with spinal-cord injuries participated in a study using this paradigm. None of them had any prior experience with BCI. Two bipolar EEG signals were recorded from electrode positions close to C3 and C4, respectively. Two different types of motor imagery (either right vs. left hand motor imagery or hand vs. foot motor imagery) were used and band power within the alpha band and the beta band were classified. The patient's task was to hit the highlighted basket (which changed side randomly from trial to trial) as often as possible. The speed was increased run by run until the patient judged it as too fast. In this way it was attempted to find the optimal speed for a maximum information transfer rate. After each run users were asked to rate their performance and to suggest whether the system operated too slow or too fast. The highest information transfer rate of 17 bits/min was reached with a trial length of 2.5 seconds (Fig 60.4, right side) (Krausz et al., 2003).

The Wadsworth BCI (Wolpaw et al., 2002) is designed to improve the communication and control capacities and quality of life in patients with severe motor disabilities. This BCI has focused primarily on EEG rhythms recorded from sensorimotor cortex to control cursor movement in one or two dimensions with the goal to select characters. Well-trained users have achieved an information transfer rate (ITR) of up to 20 to 25 bits/min, by directing a horizontally moving ball in one of up to eight different targets (McFarland et al., 2000). At this time, beside brain oscillations also other signal features as ERP components were included to improve speed and accuracy (Wolpaw et al., 2003). In a different approach, an EEG-based BCI with three mental tasks, Millan and Mourino (2003) reported an average ITR of 13 bits/min in four trained subjects.

When the amplitude of brain oscillations is used to control a BCI, the ITR is limited by the time needed for EEG desynchronization and synchronization to be detected. For exam-

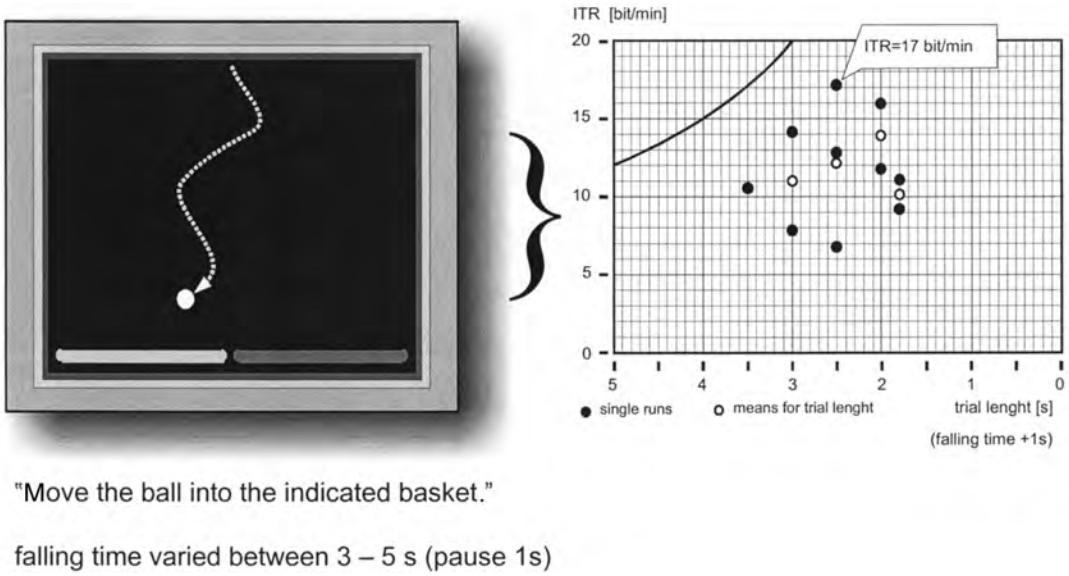


**Figure 60.4. Left side:** Graphical display of the "basket-paradigm." The subject has to direct the ball to the indicated goal ("basket"). The trial length varies across the different runs. **Right side:** Information transfer rate (ITR) for one subject in relation to trial length. The *black line* represents the maximum possible ITR for an error-free classification. (Modified from Krausz, G., Scherer, R., Korisek, G., et al. 2003. Critical decision speed and information transfer in the Graz Brain-Computer Interface. Appl. Psychophysiol. Biofeedback, in press.)

ple, in the case of alpha rhythms at least several seconds are needed for desynchronization and resynchronization to become evident. In the case of a (de)synchronization time of 3 seconds, a maximum theoretical ITR of 20 bits/min is possible with two mental tasks. The ITR can be slightly increased when, instead of alpha, faster reacting beta rhythms are used for control. But, independent of the used frequency components, the most crucial factor for obtaining a high ITR in BCI applications is the classification accuracy. When the ITR with two mental tasks and 100% classification accuracy is 12 bits/min, the ITR drops to 4 bits/min with 80% classification accuracy (Wolpaw et al., 2002).

Also of interest is the work of the Berlin group (Blankertz et al. 2003). In a first attempt they were able to predict movement preparation (right vs. left-hand finger movement) from single trial EEG by classification of the Bereitschaftspotential (readiness potential) with nearly 100% accuracy. In four subjects they reported an ITR of 6 to 10 bits/min.

## Applications

Currently, there are two important applications of a BCI. The first is to provide a new communication channel for patients severely affected by loss of all voluntary muscle control, including eye movement, and suffering, for example, from ALS or brain state stroke. The second is to restore muscle functions in patients with spinal cord injuries either to control functional electrical stimulation (FES) or to operate a neuroprosthesis or orthoses. For both applications, speed and accuracy are important.

It was demonstrated that patients suffering from advanced ALS can acquire the ability to operate a spelling device referred to as a "thought translation device" (TTD) by regulating their slow cortical potentials (Birbaumer et al., 1999). The selection of one character takes 4 seconds. During a 2-second period the user's cortical potential level is measured and compared with a 2-second baseline level. The potential difference is displayed as vertical cursor movement and used to select letters or characters. Patients with ALS were able to operate the TTD with one to two characters per minute. Over the past years more than 18 patients diagnosed with neuromuscular diseases were trained to control the TTD; in the case of a few patients the feasibility of long-term BCI use (e.g., for more than 5 years) was confirmed (Kübler et al., 2001; Neumann et al., 2003).

Moreover, it was also shown that a BCI based on oscillatory EEG changes, induced by motor imagery, can be utilized to restore communication in severely disabled people (Neuper et al., 2003). The novel aspect was that a patient, diagnosed with cerebral palsy who had lost all voluntary muscle control learned how to control, how to enhance, and how to suppress specific frequency components of the sensorimotor EEG by using a motor imagery strategy. In order for the patient to obtain control over his brain oscillations, BCI training sessions had to be conducted two times a week over a time period of several months.

In a project with a tetraplegic patient, FES resulting in hand grasp was controlled by ongoing EEG activity based on an asynchronous BCI. The patient underwent a large number of BCI training sessions with varying types of motor imagery over a period of several months (Pfurtscheller et al., 2000). At the end he was able to induce trains of 17-Hz beta oscillations focused on the electrode position near the vertex (Cz) by foot motor imagery (Fig. 60.3). These mentally induced 17-Hz oscillations were used as a simple asynchronous brain switch to generate a control signal for the operation of the FES using surface electrodes (Fig. 60.5). With this method the patient was able to grasp a glass at "will" (for a detailed description of the procedure see Pfurtscheller et al., 2003b).

## Perspectives for the Future

A clear challenge for the future is to realize more effective BCI control paradigms, offering, for instance, three-dimensional (3D) control over a neuroprosthesis or the operation of a spelling device with a speed of at least five to ten characters/minute. Both applications should be realizable by either an enhancement of the classification accuracy or the discrimination between three or more brain states.

We should note that an improvement of speed and accuracy is possible when, instead of EEG records, one would use directly cortical potential changes recorded with ECoG electrode strips or grids or even to record neuronal firing patterns using intracortical semi-microelectrode recordings.

The advantage of the ECoG over the EEG is the better signal-to-noise ratio and therefore also the easier detection of gamma activity. Recently, bursts of gamma activity between 60 and 90 Hz in ECoG recordings during self-paced limb and tongue movements were reported (Crone et al., 1999; Pfurtscheller et al., 2003a). These gamma bursts are short lasting, display a high somatotopic specificity and are embedded in the alpha and beta ERD lasting for some seconds. Patient-oriented work with subdural electrodes and ECoG single trial classification has shown initial promising results (Graimann et al., 2003; Levine et al., 2000).

Studies in monkeys have shown that 3D control is possible when multiunit activity is recorded in cortical areas. Between 32 and 96 microwires were implanted in different cortical motor areas. After a training period with distinct motor tasks, the monkeys were able to achieve 3D control over the movement of a robotic device by real-time transformation of neuronal multiunit neuronal activity (Wessberg et al., 2000). The feasibility of direct cursor control for the selection of icons or letters using an implanted neurotropic cortical electrode in patients was already demonstrated by Kennedy et al. (2000).

At this time, nearly all BCI systems (for a comprehensive review see Wolpaw et al., 2002) are cue-based or computer-driven (synchronous BCI). This means that the time window

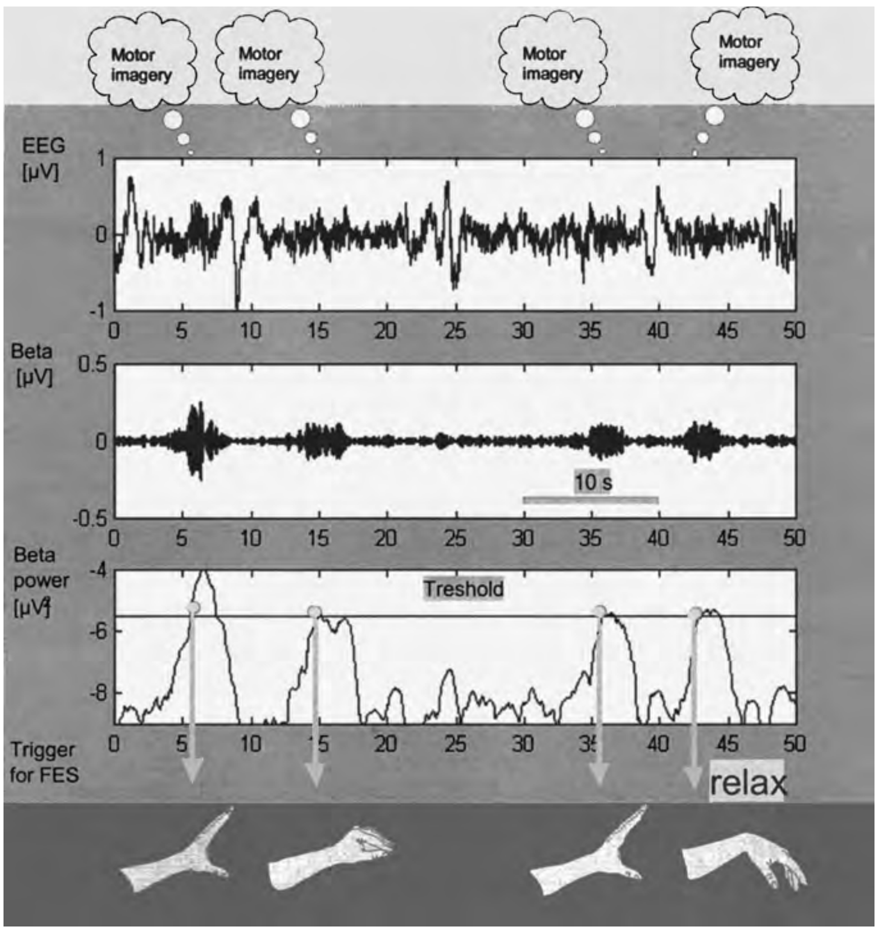


**Figure 60.5.** Examples of bipolar EEG recording (tetraplegic patient T.S.) from the vertex *(upper trace),* band pass filtered (15–19 Hz) EEG signal *(middle trace),* and band power time course (*lower trace,* arbitrary units) over a time period of about 1 minute. Each imagined foot movement induced a beta burst; depending on the threshold, a trigger pulse was initiated to control functional electrical stimulation to restore hand grasp.

where a mental task has to be recognized is predefined. An uncued or user-driven BCI (asynchronous BCI) where the EEG (ECoG) has to be analyzed and classified continuously is more complex. In this case, the major problem is to detect all true positives (hits) classification associated with predefined imagery tasks and to minimize the false-positive classification while the user is in the resting or idling state. Recently, Birch et al. (2002) reported true-positive rates of 70% and false-positive rates below 3% in subjects with high-level spinal cord injury using an asynchronous BCI and self-paced imagined movements.

One line of research has to be directed to design an application-independent, BCI-based pointing device as proposed by Mason and Birch (2003). Such a system uses a visual stimulator and is based either on P300 component (Donchin et al., 2000) or on SSVEPs (Cheng et al., 2002). The main goal of such a system is to overcome the limitation of the information transfer rate that is currently at about 20 bits/min, when a motor imagery strategy is used. Future research should also be focused on learning more about the underlying mechanisms of brain activity patterns related to motor imagery.

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