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Int. J. Human-Computer Studies 65 (2007) 460–477

International Journal of Human-Computer Studies

www.elsevier.com/locate/ijhcs

Berlin Brain–Computer Interface—The HCI communication channel for discovery

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Available online 18 January 2007

Abstract

The investigation of innovative Human–Computer Interfaces (HCI) provides a challenge for future interaction research and development. Brain–Computer Interfaces (BCIs) exploit the ability of human communication and control bypassing the classical neuromuscular communication channels. In general, BCIs offer a possibility of communication for people with severe neuromuscular disorders, such as amyotrophic lateral sclerosis (ALS) or complete paralysis of all extremities due to high spinal cord injury. Beyond medical applications, a BCI conjunction with exciting multimedia applications, e.g., a dexterity discovery, could define a new level of control possibilities also for healthy customers decoding information directly from the user's brain, as reflected in EEG signals which are recorded non-invasively from the scalp.

This contribution introduces the Berlin Brain–Computer Interface (BBCI) and presents set-ups where the user is provided with intuitive control strategies in plausible interactive bio-feedback applications. Yet at its beginning, BBCI thus adds a new dimension in HCI research by offering the user an additional and independent communication channel based on brain activity only. Successful experiments already yielded inspiring proofs-of-concept. A diversity of interactive application models, say computer games, and their specific intuitive control strategies are now open for BCI research aiming at a further speed up of user adaptation and increase of learning success and transfer bit rates.

BBCI is a complex distributed software system that can be run on several communicating computers responsible for (i) the signal acquisition, (ii) the data processing and (iii) the feedback application. Developing a BCI system, special attention must be paid to the design of the feedback application that serves as the HCI unit. This should provide the user with the information about her/his brain activity in a way that is intuitively intelligible. Exciting discovery applications qualify perfectly for this role. However, most of these applications incorporate control strategies that are developed especially for the control with haptic devices, e.g., joystick, keyboard or mouse. Therefore, novel control strategies should be developed for this purpose that (i) allow the user to incorporate additional information for the control of animated objects and (ii) do not frustrate the user in the case of a misclassification of the decoded brain signal.

BCIs are able to decode different information types from the user's brain activity, such as sensory perception or motor intentions and imaginations, movement preparations, levels of stress, workload or task-related idling. All of these diverse brain signals can be incorporated in an exciting discovery scenario. Modern HCI research and development technologies can provide BCI researchers with the know-how about interactive feedback applications and corresponding control strategies.

Keywords: Brain–Computer Interface; Scientific discovery; Electroencephalography; Digital Signal Processing; Machine learning; Bio-feedback; Control strategy; Gaming; Virtual limbs

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1071-5819/$ - see front matter
doi:10.1016/j.ijhcs.2006.11.010

1. Introduction

In the seven decades since the original publication of Berger (1929) the electroencephalogram (EEG) has been used mainly to evaluate neurological disorders and to investigate brain function. Besides, people have also speculated that it could be used to decipher thoughts or intents, such that a person will be able to control devices directly by her/his brain activity, bypassing the normal channels of peripheral nerves and muscles. However, due to the large amount of data to be analysed, it could attract serious scientific attention only in the last decade, promoted by the rapid development in computer hardware and software, as nowadays it is possible to distribute tasks of a complex system over different computers communicating with each other and to process acquired data in a parallel manner and in real-time.

Moreover, recent research in digital signal processing and data analysis provide the possibility to develop intelligent and automatically adapting systems, which do not rely on prior knowledge about the user, but set-up its model at first contact and online. Obviously, a test person, interacting with a computer application, generates distinct spatio-temporal neuroelectric patterns in cortices of her/his brain. In particular, the cerebral processing of visual or auditory information provided by the monitor screen or loudspeakers produces specific EEG patterns in the primary visual or, respectively, auditory sensory cortices. Those can easily be observed and classified by EEG recorded over the respective cortex. Notably, further cognitive processing of this information is widely distributed across the cortex posing a hard challenge for non-invasive recording techniques to disentangle the contributions from different cortical processing modules. Thus, while the intentions to control the system by performing some motor, i.e., muscle activity, emerges inside the brain's high-level decision centers, finally they take their way to the primary motor cortices, such that rising neural activity can be read out from surface EEG electrodes placed over the motor brain regions, which fortunately have a regular somatotopic arrangement, i.e., the body is represented in a orderly topography (Penfield and Rasmussen, 1950).

Due to physical limits in spatial resolution of surface EEG, the discrimination of nearby located cortical areas represents a challenging problem for data analysis, since each single electrode acquires superposed data from within a certain neighbourhood radius, where many originally different signals are superimposed.

Currently, modern HCI and multimedia technologies address only a subset of I/O channels humans use for interaction with a computer application or a device. Those demand mainly motor (joystick, pedal), visual (graphics, animation) and acoustic (sound, music, speech) senses. Recent research tries to include also olfaction (Harel et al., 2003), tactile sensation (MacIntyre and Feiner, 1996; Hardwick et al., 1996), interpretation of facial emotions (Pantic and Rothkrantz, 2000) and gestures (Pentland, 1995; Quek et al., 2002). Since all these information streams pass its own interface (hand/skin, eye, ear, nose, muscles) yet indirectly converge or emerge in the brain, the investigation of a direct communication channel between the application and the human brain should be of high interest to HCI researchers (Ebrahimi et al., 2003).

Furthermore, Steriadis and Constantinou (2003) state, that development of Human–Computer Interfaces (HCIs) for people with severe disabilities, e.g., amyotrophic lateral sclerosis (ALS), or quadriplegia due to high spinal cord injury or brainstem stroke patients, is an important issue for integrating them into an emerging Information Society. Due to the damage of normal communication paths, e.g., peripheral nerves and muscles that are required for interaction with computers or other devices, information on intention of movement execution can be extracted from the last faultless communication stage. Green et al. (1999) have shown that motor and sensory cortices of patients with amputated extremities, e.g., arms or legs remain intact and produce normal spatio-temporal activation patterns on intentions to move the absent part of the body, as they can be observed in healthy people. Accordingly, a technique for recognizing and deciphering those patterns and translating them into device control commands might serve as the core for a wide variety of applications in the field of HCI, which will provide to handicapped people the ability to communicate with their environment or to control various devices.

A special role must be assigned to the intelligibility of feedback. Ramachandran (1999) reports that patients following lateral hemisphere stroke display an indifference to objects and events in the contralateral side of the world (neglect). Looking into a mirror and imagining moving the absent arm, which is a reflection of the other intact arm helps to allay the phantom pains and accelerates the recovery from neglect. Producing natural feedback on a computer screen with actions, correlated to the intentions of the patient might have similar helpful consequences for the convalescence.

Finally, talking about bio-feedback as the core of matter, one cannot avoid mentioning the recently developed commercial system "The Journey to the Wild Divine" (www.wilddivine.com). This incorporates different bio-signals which can be acquired with inexpensive devices and in home environment, like heart beat pulse, skin surface conduction measured at the fingertips, breath frequency and depth, etc. to train relaxation and meditation. This incorporates sumptuous graphics and animations to visualize the user's bio-signals in a relaxing gaming scenario. Its greatest advantage is that it is made amendable to a wide range of users. However, it forces the user to generate a certain bio-signal pattern, rather than employing some machine adaptation technique for fitting the user's current condition and learning to recognize the user's intension. Moreover, it is indistinct up to what extend it is able to employ brain activity as an independent control channel. Undisputable, this product marks a great step in bio-feedback research and development; however, its scientific contribution to the area of signal processing and brain–computer interfacing is limited.

In Section 2 we give a short introduction in state-of-the-art in BCI, and in Section 3, we introduce a novel communication channel that can be used in HCI as based on a new technique for information retrieval directly from the brain. This is followed by a demonstration of a set of interactive applications used for bio-feedback, in Section 4. Section 5 concludes with a discussion on future perspectives of BCIs in the fields of human–computer interaction, control and discovery.

2. State of the art in BCI

A recent review on BCI defines a Brain–Computer Interface as *a system for controlling a device, e.g., computer, wheelchair or a neuroprosthesis by human intentions, which does not depend on the brain's normal output pathways of peripheral nerves and muscles* (Wolpaw et al., 2002).

There are several non-invasive methods of monitoring brain activity encompassing functional Near-infrared Imaging (fNIR), Positron Emission Tomography (PET), functional Magnetic Resonance Imaging (fMRI), Magnetoencephalography (MEG) or Electroencephalography (EEG) techniques, which all have advantages and shortcomings.[1] Notably, EEG alone yields data that is easily recorded with comparatively inexpensive equipment, is rather well studied and provides high temporal resolution. Thus, it outperforms remaining techniques as an excellent candidate for BCI. EEG-based BCI systems can be subdivided into several groups according to the electrophysiological signals they use.

2.1. Visual-evoked potentials

Visual-evoked potentials (VEPs) define a *dependent* BCI, i.e., they depend on oculomotor control of gaze direction, such that activity in the normal information pathways, e.g., peripheral nerves and muscles is needed to generate the brain activity. Sutter (1992) described a brain response interface (BRI) applying it as a keyboard interface: by selecting a symbol from a set of 64 proposed in an 8×8 matrix by focusing on it volunteers were able to type 10–12 words/min. Symbols were changing their colour or flashing with a certain frequency, which induces a distinct spatiotemporal pattern in the visual cortex of the user's brain. However, this method requires stable control over oculomotor muscles, needed for focusing a letter. A dependent BCI is essentially an alternative method for detecting messages carried out in the brain's normal output pathways, but does not give the user a new communication channel that is independent of conventional channels.

[1]Please note that this list of currently available technologies for measuring and visualizing brain activity does not claim for any exhaustiveness or completeness.

2.2. P300-based BCI

BCI systems are defined to be *independent*, if they do not rely on any muscular activity, if the message is not carried by peripheral nerves and muscles, and, furthermore, if activity in these pathways is not needed to generate the brain activity (e.g., EEG) that does carry the message. For example, a subject waiting for the occurrence of a rare stimulus on the background of a series of standard stimuli evokes a Positive peak over parietal cortex about 300 ms (*P300*) after appearance. Donchin and Smith (1970) presented a P300-based BCI used for typing of ca. 5 letters/min. However, those techniques remain limited to letter selection paradigms, similar to that one described in the previous subsection.

Approaches for independent BCIs are of greater theoretical interest than for dependent BCIs, because they offer the brain a completely new output pathway and are likely to be more useful for people with most severe neuromuscular disabilities.

2.3. BCI based on motor imagery

In Albany, New York, Jonathan Wolpaw directs the development of a BCI system that lets the user steer a cursor by oscillatory brain activity into one of two or four possible targets (Wolpaw et al., 1991). In the first training sessions most of the subjects use some kind of motor imagery, which is then, during further feedback sessions, replaced by adapted strategies. Well-trained users achieve hit rates of over 90% in the two-target set-up; however, each selection typically takes 4–5 s.

The lab in Graz of Gert Pfurtscheller develops a BCI system that is based on event-related modulations of the μ- and/or the central β-rhythm of sensorimotor cortices. For control paradigm the focus is on motor preparation and imagination. Feature vectors calculated from spontaneous EEG signals by adaptive auto-regressive modelling are used to train a classifier. In a ternary classification task accuracies of over 96% were obtained in an offline study with trial duration of 8 s (Peters et al., 2001).

2.4. Event related (de-)synchronization

Physiologically meaningful signal features can be extracted from various frequency bands of recorded EEG, e.g., Pfurtscheller (1999) reports that μ and/or β rhythm amplitudes serve as effective input for a BCI. Movement preparation, followed by execution or even only motor imagination is usually accompanied by a power decrease in certain frequency bands, labelled as event-related desynchronization (ERD); in contrast, their increase after a movement indicates relaxation and is due to an event-related synchronization (ERS) in firing rates of large populations of cortical neurons. Table 1 summarizes frequency bands (marginal frequency values are highly

Table 1
Frequency bands

Band	Frequency (Hz)	Occur while/indicate
δ	0.5–3.5	Movement preparation
θ	3.5–8	Memory
α (μ)	8–13	Relaxation, sensory idling
β	13–22	Motor idling
γ	22–40	Feature binding

subject-specific) and neurophysiological features they are assumed to encode.

2.5. Slow cortical potentials

Slow cortical potentials (SCP) are voltage shifts generated in cortex lasting over 0.5–10 s. Slow negativation is usually associated with cortical activation, e.g., evoked by the implementation of a movement or by the accomplishment of a mental task, whereas positive shifts indicate cortical relaxation (Birbaumer, 1997). Further studies showed that it is possible to learn SCP control. Consequently, it was used in Birbaumer et al. (1999) to control movements of an object on a computer screen in a BCI referred to as *Thought Translation Device* (TTD). After repeated training sessions over months, through which patients achieve accuracies over 75%, they are switched to a letter support programme, which allows selection of up to 3 letters/min.

A new letter selection protocol, involving a predictive algorithm that uses a set of first letters of a word to select the whole word from a lexicon which adapts to the user's vocabulary simultaneously, increases the communication rate and provides Internet access to a disabled user (Birbaumer et al., 2000).

2.6. Invasive methods for BCI

Using information recorded invasively from an animal brain Nicolelis and Chapin (2002) report a BCI able to control a robot. Four arrays of fine microwires penetrate the animal's scull and connect to different regions inside the motor cortex. A robotic arm remotely connected over the Internet implements roughly the same trajectory as the owl monkey gripping for food. This invasive technology allows the extraction of signals with fine spatial and temporal resolution, since each microelectrode integrates firing rates of few dozens of neurons. However, to make a BCI attractive to an everyday-user it should be non-invasive, fast mounted and leave no marks.

3. The Berlin Brain–Computer Interface (BBCI)

This section presents an independent non-invasive EEG-based online-BCI, developed at Fraunhofer FIRST and the Neurophysics Group of the Charité—Universitaetsmedizin Berlin that overcomes limitations mentioned above. BBCI

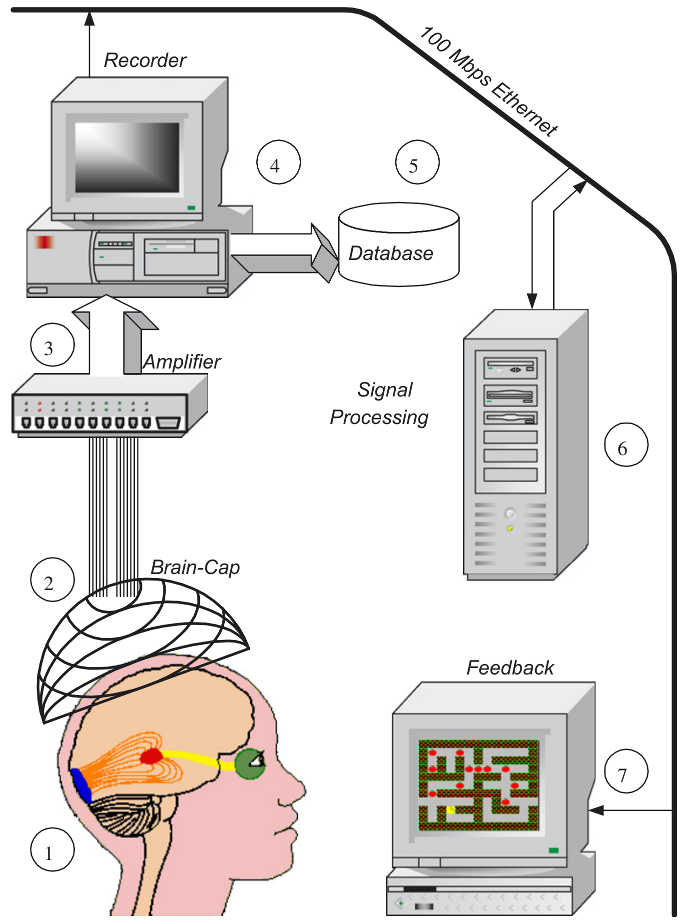

Fig. 1. Distributed software design of the BBCI system.

is based on lateralized readiness potentials (LRP), which is a form of SCP and appear during movement preparation. Interestingly, the intrinsic movement execution is not essential since LRP variants can be observed also for imagined movements in healthy test persons. Note, however, that the intention of a person to move her/his amputated arm is not identical with imagined arm movements of a healthy person because in the latter case an additional "no-go" or "veto" signal is required to prevent the actual motor performance. Therefore, the BBCI focuses on the preparation of real, rather than imagined movements.

The enormous amount of data to be processed in a limited time forced the distribution of processing tasks over several computers communicating via client–server interfaces. Moreover, this distributed concept allows advantageous replacement of single modules according to particular communication protocols. Fig. 1 illustrates the distributed software design of the BBCI system.

The volunteer user (1) is facing a computer screen. A drapery brain-cap (2) furnished with 128 electrodes is put on her/his head. Four flat cables of 32 wires each connect the cap with four amplifiers (3), which also perform an A/D-conversion and transmit the acquired EEG at sampling rate of 5 kHz and accuracy of 16 bits via a fiber

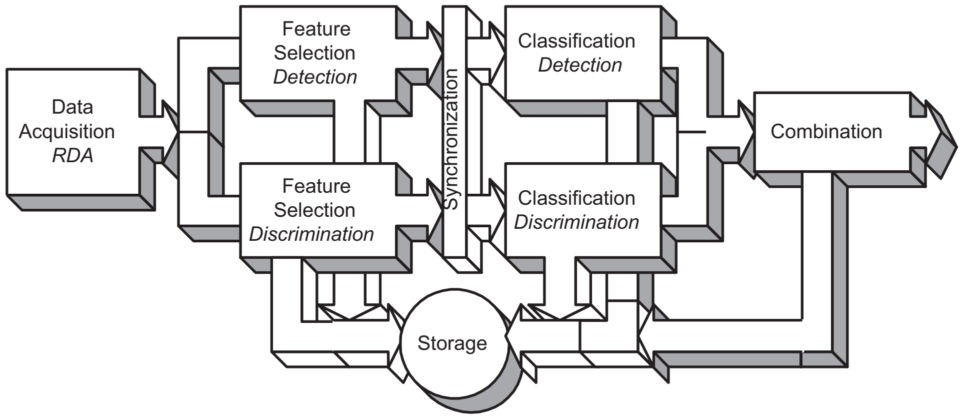

Fig. 2. Parallel manner of the BBCI's data processing unit.

optic cable (to avoid electromagnetic interferences) to the recorder PC (4). The recorder performs some predefined simple preprocessing operations, i.e., subsampling to 1 kHz, optional low/high/band-pass or notch filters, and stores the data in raw format for later offline analysis into the database (5). Additionally it acts as Remote Data Access (RDA) server, which allows up to 10 client connections and serves one data block of acquired EEG and auxiliary information, e.g., control signals or event markers, each 40 ms. A second computer (6) runs a corresponding client, which performs, after data acquisition, some preprocessing steps for feature selection (details in Section 3.4) in a parallel manner. For the detection and the discrimination of user actions two separate non-blocking threads were employed. Each is followed after an optional synchronization by a classification step of the current extracted feature vector (details in Section 3.5). Finally, a combiner joins the two-classifier results and produces a control command. Fig. 2 illustrates the parallel approach of data processing. The online classifier (6) acts as a server for various feedback clients (7) and serves each 40 ms the control command that has been produced by the combiner.

The feedback client is an interactive application that may run on a separate computer and acquires the control commands produced by the combiner module of the data processing server. It is conceived to rely on simple control, e.g., left/right movements, which may be expressed by a small command set, and should give the user a feeling of being inside the simulation. Currently, we employed simple computer games like Pacman or Tele-Tennis, however, other more sophisticated and challenging applications, like Tetris or manoeuvreing through a Virtual Reality (VR) maze are conceivable.

3.1. Data acquisition

We recorded brain activity with multi-channel EEG amplifiers (Brain Products™, Munich) using 128 channels from a cap with Ag/AgCl Electrodes (∅ of the contact region is 5 mm). Additionally, surface electromyogram (EMG) signals, which detect muscle activity at both forearms, as well as horizontal and vertical electrooculogram (EOG) signals, which reflect eye movements, were recorded. All signals were band-pass filtered between 0.05 and 200 Hz and sampled at 1000 Hz. For online analysis, the data signals were then subsampled to 100 Hz to minimize the data processing effort.

The labels of electrodes are composed of some letters and a number. The letters refer to anatomical structures (Frontal, Parietal, Occipital, Temporal lobes and Central sulcus), while the numbers denote sagittal (anterior–posterior) lines. Odd numbers correspond to the left hemisphere, while even numbers to the right; small '*z*' marks electrodes on the central sagittal line. Labels with 1 or 2 capital letters correspond to the 64 electrodes of the extended international 10–20-system as defined in Sharbrough et al. (1991) while labels with three capital letters were composed from the neighbouring electrode labels and denote additional channels in a 128-channel set-up. EEG activity is measured against the reference electrode (Ref) mounted on the nasion, while the ground electrode (Gnd) is mounted on the forehead. Locations of the electrodes and corresponding labels are illustrated in Fig. 3.

The voltage measured by the electrodes is very low and fluctuates rapidly within the range of $\pm 100\,\mu V$ around a baseline. Electrical noise from the surrounding environment (mainly 50 Hz, resp., 60 Hz power outlet frequency) interferes with the data via connecting wires, which act as small "antennas". To assure low impedances between the electrodes and the scalp (desired below $5\,k\Omega$), electrolyte gel is filled into each electrode before experiments start.

3.2. Task and its neurophysiology

We let our subjects (all without neurological deficits) take a binary (left/right hand) decision coupled to a motor output, i.e., self-paced typewriting on a computer keyboard. Using multi-channel scalp EEG recordings, we analyse the single-trial differential potential distributions of the Bereitschaftspotential (BP/Readiness potential) preceding voluntary (right or left hand) finger movements over

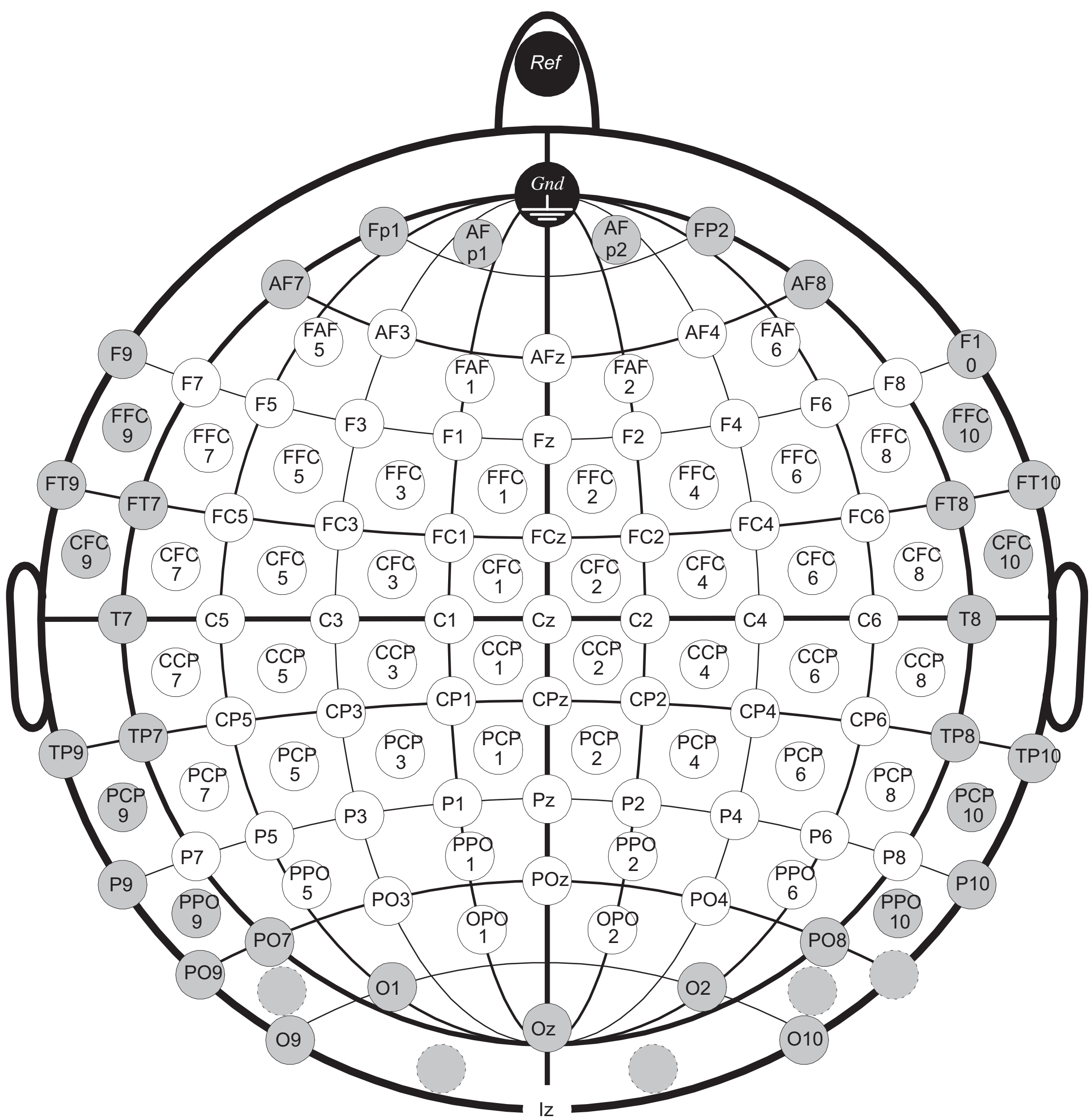

Fig. 3. Locations of electrodes and labels of the corresponding channels.

the corresponding (left/right) primary motor cortex. As we study brain signals from healthy subjects executing real movements, our paradigm requires a capability to predict the laterality of imminent hand movements prior to any EMG activity to exclude a possible confound with afferent feedback from muscle and joint receptors contingent upon an executed movement.

The basic BBCI idea is focusing on control applications, such as ''virtual keyboard typing'', that can be conceived as potentially resulting from a natural sequence of motor intention, followed by preparation and completing by the execution. Accordingly, our neurophysiological approach aims to capture EEG indices of preparation for an immediately upcoming motor action. At present, we exploit the BP, i.e., a slow negative EEG shift, which develops over the activated motor cortex during a period of about 1 s prior to the actual movement onset; it is assumed to reflect mainly the growing neuronal activation (apical dendritic polarization) in a large ensemble of pyramidal cells. Previous studies of Lang et al., 1989 and Cui et al. (1999) showed that in most subjects the spatial scalp distribution of the averaged BP correlates consistently with the moving hand (focus of brain activity is contralateral to the performing hand).

The upper part of Fig. 4 shows Laplace filtered EEG around the left and right hand motor cortices (electrodes C3 and C4) within a time range of [−450:200] ms relative to the key tap, averaged selectively for left-hand vs. right-hand taps. The grey bars indicate a 100 ms baseline correction. The lateralization of BP is clearly specific for left, resp., right finger movements. Four potential maps show the scalp topographies of the BP averaged over time

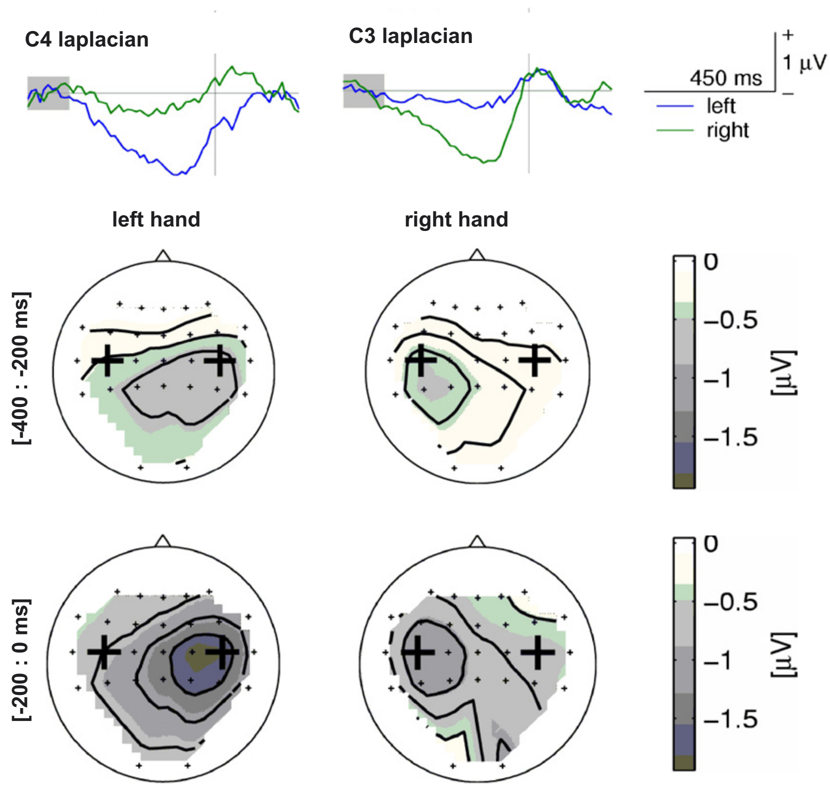

Fig. 4. Averaged Lateralized Readiness Potentials (LRP).

windows (upper) before movement preparation and (lower) when BP reaches its maximum negativation, again averaged over left-hand and right-hand taps separately. Bold crosses mark electrode positions C3 and C4.

We would like to emphasize that the paradigm is shaped presently for fast classifications in normally behaving subjects and thus could open interesting perspectives for a BCI assistance of action control in time-critical behavioural contexts. Notably, also a possible transfer to BCI controlled by paralyzed patients appears worthwhile to be studied further because these patients were shown to retain the capability to generate BPs with partially modified scalp topographies (Green et al., 1999).

3.3. Training procedure

The Leitmotiv of BBCI is: "*Let the machines learn!*", thus the user should invest only a minimum of time for training the BBCI algorithms: The training procedure described here serves for "teaching the machine" and adjusting its model parameters to better match the user and her/his brain signal's properties. During the training procedure we acquire example EEG from the user while performing a certain task, e.g., execution or imagination of left vs. right hand movement of the index or pinky fingers. During the training session the user is instructed to sit comfortably and, as far as possible, to omit any muscular artifacts, like biting, gulping, yawning, moving the head, arms, legs or the whole body. These would induce electromyographic (EMG) noise activity that interferes with EEG signals, such that the signal-to-noise-ratio (SNR) decreases. Eye movements are to be minimized for the same reason. To prevent possible (involuntarily) cheating, e.g., producing eye movements correlated with the performed tasks, vertical and horizontal EOG are recorded, which can also be used for artifact correction, i.e., cleaning up EEG signals of interfering EOG by a weighted subtraction.

The training is performed in 3–4 sessions, each of about 7 min, as illustrated in Fig. 5. Tasks are performed for a period of 6 min repeatedly with an interval of 0.5–2 s. All training sessions may be performed in two experimental kinds: (i) imagined, i.e., queried, (ii) executed, i.e., self-paced: In the executed task experiment we acquire response markers via keyboard, while the user determines her-/himself which movement to perform next. During the imagined task experiment a visual cue indicates the movement, which has to be executed on the next auditory beat produced by a digital metronome. Both stimuli place corresponding markers into the data, stored with a time stamp.

To train the learning machine and adjust its parameters, we select time series of EEG activity acquired within a certain time region before the marker, which gives the training sample its label. We search for event markers in the acquired data; these markers are (i) keyboard taps as responses for executed movements, or (ii) a combination of the visual cue with the metronome beat stimuli for imagined experiments. We then examine each marker for affiliation to one of the classes of interest. Each class of interest covers its own sample-selection parameter set $SSP = (\{mrk\}, n, t_{\mathrm{d}}, t_{\mathrm{i}})$, where a set of marker labels *mrk* identifies the affiliation of markers to classes, n gives the number of training samples to be selected from the data, t_{d} and t_{i} are time constants indicating the delay of the initial sample and the inter-sample interval. Beside the classes indicating action, e.g., execution or imagination of a movement, which in Fig. 6 provide samples **1a**, **2a** and **3a**, an additional class indicating rest is introduced. This provides in an analogue manner (incorporating t'_{d} and t'_{i} time constants that indicate the delay of the initial rest-sample and the inter-sample interval) training samples **1r** and **2r** that are used together with action samples for determining the detection of the task accomplishment, though we use action samples only, for determining the discrimination of which task has been completed. For sample selection in the training procedure, negative time constants are preferred, positive are allowed, however, they make no sense for online analysis. Special attention must be paid in fast-pace experiments to the issue that samples of the rest class do not intersect with action class samples of the preceding event marker, as they should not include any information about action.

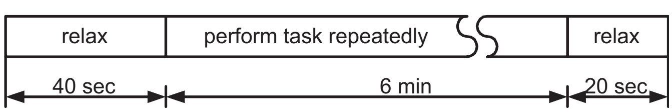

Fig. 5. Set-up of a single training session.

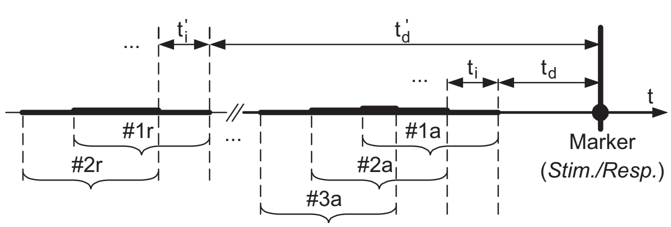

Fig. 6. Selection procedure for training samples.

3.4. Preprocessing and feature selection

To extract relevant spatiotemporal features of slow brain potentials we subsample signals from all or a subset of all available channels and take them as high-dimensional feature vectors. We apply a special treatment because in pre-movement trials most information is expected to appear at the end of the given interval. Starting point of this treatment are epochs of 128 data points (width of a sample window) of raw EEG data, corresponding to 1280 ms as it is depicted in Fig. 7(a) for a single EEG channel from -1400 to -120 ms (t_{d}) relative to the timestamp of the desired event marker. To emphasize the late signal content, we first multiply the signal by a one-sided cosine function (1), as shown in Fig. 7(b).

$$\forall n = 0, \ldots, 127 : w(n) := 0.5 \cdot \left(1 - \cos\left(\frac{n\pi}{128}\right)\right). \tag{1}$$

A Fast Fourier Transformation (FFT) filtering technique is applied to the windowed signal. From the complex-valued FFT coefficients all are discarded but the ones in the pass-band (including the negative frequencies, which are not shown); cf. Fig. 7(c). Transforming the selected bins back into the time domain gives the smoothed signal of which the last 200 ms are subsampled at 20 Hz by calculating means of consecutive non-overlapping intervals, each of 5 samples, resulting in 4 feature components per channel, see Fig. 7(d).

3.5. Linear methods for classification

In BCI research it is very common to use linear classifiers, but although linear classification already uses a

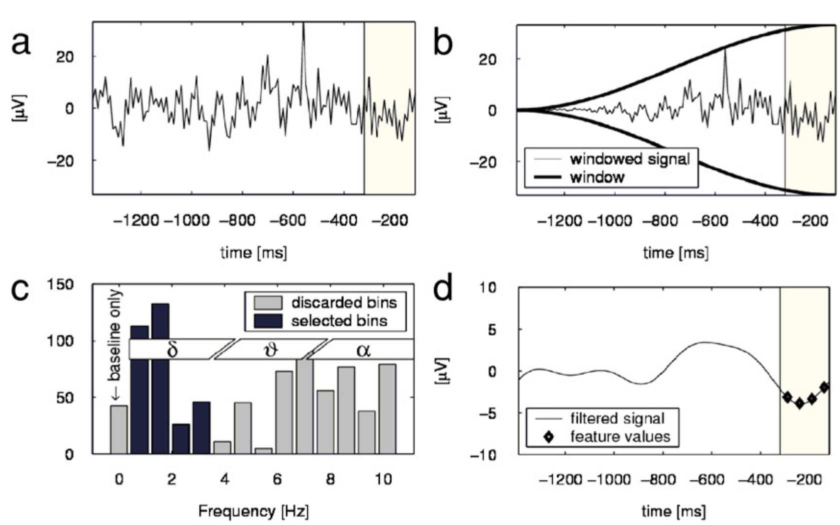

Fig. 7. Preprocessing procedure.

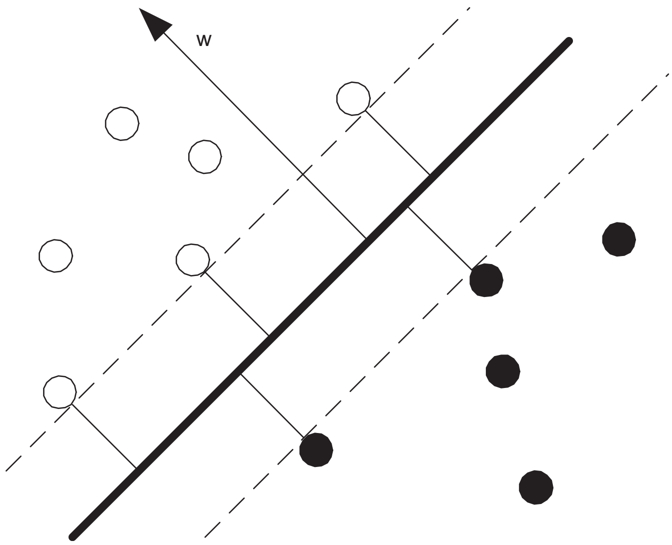

Fig. 8. Linear classifier and margins. From Müller et al. (2001).

very simple model, the analysis can still go wrong if the underlying assumptions do not hold, e.g., in the presence of outliers or strong noise, which are situations very typically encountered in BCI data analysis. We will discuss these pitfalls and point out ways around them.

Let us first fix the notation and introduce the linear hyperplane classification model upon which we will rely mostly in the following (cf. Fig. 8). In a BCI set-up we measure $k = 1 \ldots K$ samples $\boldsymbol{x}_k$, where $\boldsymbol{x}$ are some appropriate feature vectors in n-dimensional space. In the training data we have a class label, e.g., $y_k \in \{-1, +1\}$ for each sample point $\boldsymbol{x}_k$. To obtain a linear hyperplane classifier

$$y = \mathrm{sign}\left(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b\right), \tag{2}$$

we need to estimate the normal vector of the hyperplane $\boldsymbol{w}$ and a threshold b from the training data by some optimization technique. On unseen data $\boldsymbol{x}$, i.e., in a BCI feedback session, we compute the projection of the new data sample onto the direction of the normal $\boldsymbol{w}$ via Eq. (2), thus determining what class label y should be given to $\boldsymbol{x}$ according to our linear model.

A linear classifier is defined by a hyperplane's normal vector $\boldsymbol{w}$ and an offset b, i.e., the decision boundary is $\{\boldsymbol{x}|\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}+b=0\}$ (thick line). Each of the two half-spaces defined by this hyperplane corresponds to one class, i.e., $f(\boldsymbol{x}) = \mathrm{sign}(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x} + b)$. The margin of a linear classifier is the minimal distance of any training point to the hyperplane. In this case it is the distance between the dotted lines and the thick line (cf. Fig. 8).

3.5.1. Large margin classification

For linearly separable data there is a vast number of possibilities to determine $(\boldsymbol{w}; b)$, that all classify correctly on the training set, however, that vary in quality on the unseen data (test set). An advantage of the simple hyperplane classifier is that procedures have been established, e.g., Duda et al. (2001); or Vapnik (1995), on how to select the optimal classifier $\boldsymbol{w}$ for unseen data.

Linear Support Vector Machines (SVM) realize the large margin by determining the normal vector $\boldsymbol{w}$. The one particular strength of SVMs is that they can be turned into nonlinear classifiers in an elegant and effective way that is extensively described in Vapnik (1995), Schölkopf (1997), and Mika et al. (2001).

3.5.2. Fisher's discriminant

The event related potential (ERP) features are superpositions of task-related and many task-unrelated signal components, e.g., background auditory, visual or receptional noise or task independent thoughts. The mean of the distribution across trials is the non-oscillatory task-related component, ideally the same for all trials. The covariance matrix depends only on task-unrelated components. Our analysis showed that the distribution of ERP features is indeed normal. The important observation here is that the covariance matrices of both classes (left/right movements) look very much alike (Blankertz et al., 2003). This property of the ERP data set proposes the application of the Fisher's Discriminant as the classificator.

The Fisher's Discriminant is searching for a separating hyperplane which subdivides the feature space into two classes, optimizing its model parameters in two ways: (i) it maximizes the distance between the centers of mass of the two classes (inter-class variance) and (ii) minimizes the variances of the data inside each class (intra-class variances). The principal separation procedure used by RFD is illustrated in Fig. 9.

Several other regularized linear classification procedures, like Linear Perceptron with weight decay or Linear Programming Machines (LPM) have been employed for this task in Blankertz et al. (2002a, b); however, no significant difference in classification accuracy could be determined. The major advantage of the RFD-based classifier is due to its lower computational costs, such that the gain in performance could be maximized. As well several nonlinear classifiers, e.g., Quadratic Discriminant Analysis (QDA) or SVMs with Gaussian kernels, as proposed in (Mika et al., 2003), have been applied, however, their classification accuracy was seldom higher than that of the best linear classifiers, often they performed even worse. This fits with our experience that the ERP features of different classes (e.g., left and right hand) of motor trials are Gaussian distributed with equal covariance matrices. Thus, in this case the classes are linear separable and hence linear classifiers are more appropriate. Of course, nonlinear classifiers can also learn linear problems, but due to the increase of complexity of their models they are more susceptible to noise which is a principle concern in EEG data (see also the discussion of this issue in Müller et al. (2003) and Krepki (2004)).

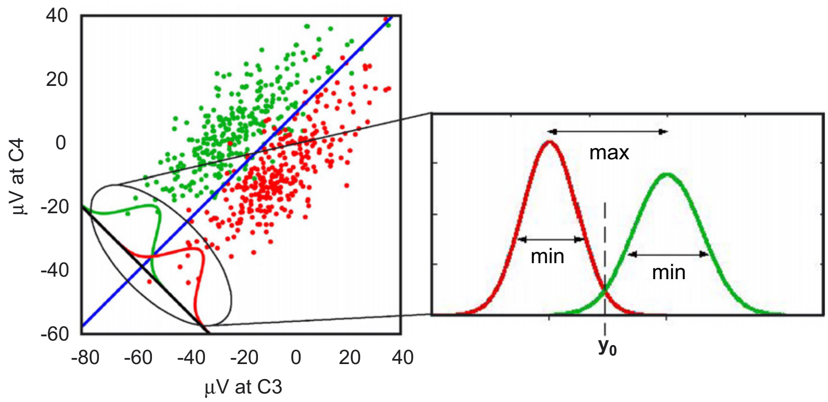

Fig. 9. Principal separation procedure by the Regularized Fisher's Discriminant (RFD) for a 2-class problem.

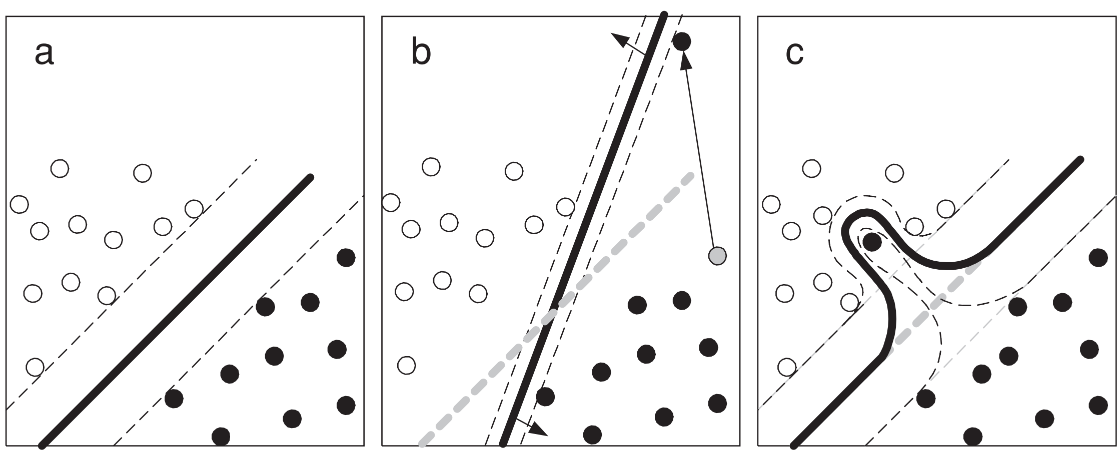

Fig. 10. The problem of finding a maximum margin "hyper-plane" on reliable data (a), data with an outlier (b) and with a mislabelled pattern (c). From Rätsch et al. (2001).

3.5.3. Regularization and non-robust classifiers

Linear classifiers are generally more robust than their nonlinear counterparts, since they have only limited flexibility (less free parameters to tune) and are thus less prone to over-fitting. Note, however, that in the presence of strong noise and outliers even linear systems can fail. In Fig. 10, one can clearly observe that one outlier or strong noise event can change the decision surface drastically, if the influence of single data points on learning is not limited. The solid line in Fig. 10 shows the resulting decision line, whereas the dashed lines mark the margin area. In the middle and on the right the original decision line is plotted grey. Illustrated is the noise sensitivity: only one strong noise/outlier pattern can spoil the whole estimation of the decision line.

Although this effect can yield strongly decreased classification results for linear learning machines, it can be even more devastating for nonlinear methods. A more formal way to control one's mistrust in the available training data is to use regularization, as it is proposed in Poggio and Girosi (1990) and Orr and Müller (1998) and elsewhere. Regularization helps to limit (i) the influence of outliers or strong noise (e.g., to avoid Fig. 10b), (ii) the complexity of the classifier (e.g., to avoid Fig. 10c) and (iii) the raggedness of the decision surface (e.g., to avoid Fig. 10c).

The cross-validation procedure that is employed for regularization purposes in the BBCI system is discussed in more detail at the beginning of Section 4.

3.6. Bio-feedback

Finally, an interactive application, running on a separate computer, receives combined results of classification via an asynchronous client–server interface based on the User Datagram Protocol (UDP) and acquires them in a temporal queue. It examines the queue repeatedly for stationary past signals persisting for a certain time length, i.e., a Command Activation Term (CAT), and emits the command corresponding to the class label of the classification result (left/right/rest). After a command has been emitted, it then falls into "relaxation" for a certain time period, i.e., Command Relaxation Term (CRT), which should be at least as long as the CAT. During this period combiner outputs remain being collected in the queue, but further command emissions are suppressed.

This procedure, for three classes: left (black), right (grey) and rest (dashed) is illustrated in Fig. 11. Here the combiner yields the class label (denoted as colour of bars) and the fuzzy values $\tilde{P}_{\max} = \max_i \tilde{P}_i$ of the most likely recognized class (depicted as amplitude) distributed over time at a frequency of 25 Hz. CAT is set to 10 periods (400 ms), and CRT is set to 14 periods (560 ms).

This flexible set-up allows individual adjustments for the user and the control strategy of the bio-feedback application: (i) long CAT helps to avoid false-positively emitted commands; (ii) short CAT, in contrast, allows fast emission of commands, i.e., before the real movement is executed; (iii) intraindividually adjusted CRT prevents erroneous emissions and, respectively, allows volitional successive emissions of the last command. These parameters depend strongly on the user and should be set initially to values calculated from the results of the application of trained classifier to the training data. At starting point CAT_0 may be set to the median length of the stable signal containing a marker of the same action class, and CRT_0 to a value larger than CAT_0 by twice the amount of the standard deviation of the distribution of lengths of stable signals. The values of CAT and CRT should then be adjusted according to the user's demand.

The underlying interactive feedback application should be intuitive, simple to understand, and the control strategy should give the user a feeling of natural acting; however, it should require a small (at present: binary) control set of commands, i.e., left-turn/right-turn, avoid fast animation and high-contrast changes to prevent or at least to minimize spoiling of data affected by artifacts, e.g., brisk movements of eye, head or body. An issue of particular importance for a fast pacing of control commands is a "natural mapping" of the action required in the virtual reality scenario to the "action space" of the human operator, which is coded in egocentric coordinates. To this end the on-screen environmental perspective must continuously represent the viewing direction of the human operator, so that, e.g., a selection of the option of right-turn can be addressed by the intention to move the right hand and vice versa.

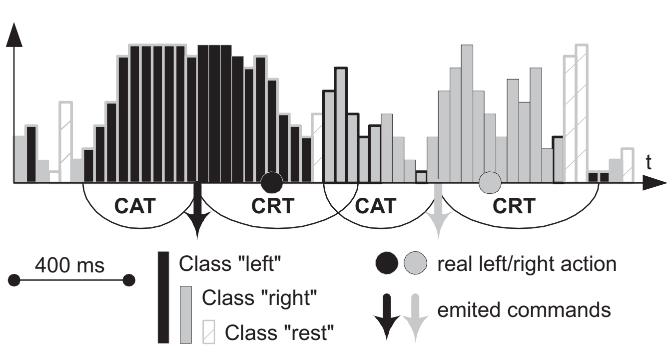

Fig. 11. Time structure of the command emission queue.

3.7. On erroneously emitted commands

It is a well-known finding in human psychophysics, that a subject's recognition of having committed a response error is accompanied by specific EEG variations that can easily be observed in averaged ERPs. Blankertz et al. (2002a, b) present a pattern recognition approach that allows for a robust single trial detection of this *error potential* from multi-channel EEG signals. It is an elegant approach to overcome the problem of low classification accuracy by a response checking mechanism that is based on the subject's brain signals themselves, such that those persons benefit most who otherwise can only reach a modest BCI control because of a substantial fraction of classification errors. The ERP after an error trial is characterized by two components: a negative wave (N_E) with a fronto-central maximum, and a following broader positive peak (P_E) with a centro-parietal maximum. N_E seems to initiate some kind of comparison process since it is present also in most correct trials, while P_E seems to indicate brain's reaction of recognizing that the subject's action was erroneous. Fig. 12 shows average miss-minus-hit EEG-traces at electrodes along the vertex and the scalp EEG potential topographies around that region.

To assess the potential value of error detection for improving BCI transmission rates we calculate the amount of information that can be read out from a 2-class decision experiment ($N = 2$) with a BCI providing an accuracy of 85% ($p = 0.85$) using Shannon's information criterion (3):

$$I(p) := \log_2 N + p \log_2 p + (1-p)\log_2 \frac{1-p}{N-1}, \tag{3}$$

$I(0.85) = 0.39$ bits per selection for the system alone, however, it can be improved by more than 75% to 0.69 bits per selection in a system involving an error correction method working with 20% false-negative ($FN = 0.2$) and 3% false positive ($FP = 0.03$), where the accuracy of the improved system can be calculated by

$$\begin{aligned} p'(p, FP, FN) &= p \cdot (1 - FP) + (1-p) \cdot (1 - FN) \\ &= 0.94, \text{ and } I(p') = 0.69 \text{ bit} \end{aligned} \tag{4}$$

Note, that this is only a theoretical value used as BCI performance measure. Achievement of this information transmission rate would require a specific coding of the information by the BCI user. Fig. 13 shows a plot of the theoretical information rate (I) in a two-class experiment as a function of the accuracy (p) of the pure BCI system with and without the error correction procedure working with an assumed rate of 20% of false negatives and 3% of false positives. Obviously the gain gets less, the higher the original BCI accuracy is; note that with the assumed parameters an error correction approach is useful, as long as the pure BCI accuracy is below 96%.

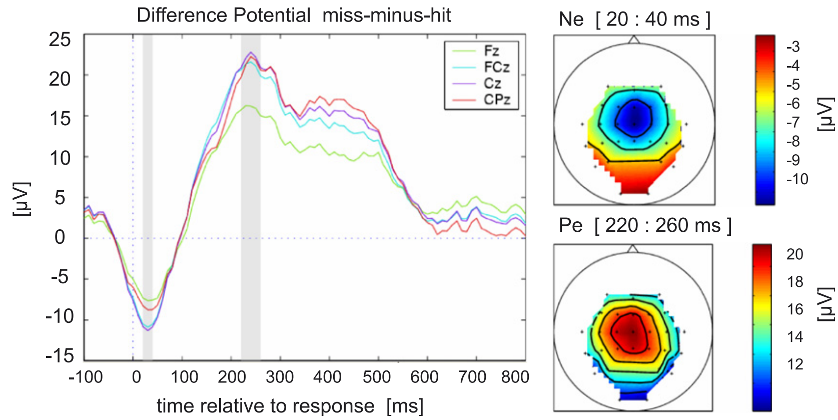

Fig. 12. Averaged miss-minus-hit error-related potentials and the corresponding scalp topographies.

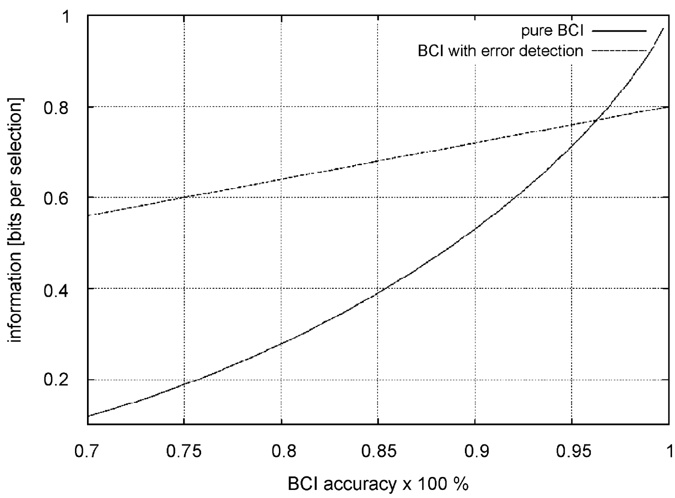

Fig. 13. Improvement of the BCI system by the error correction procedure.

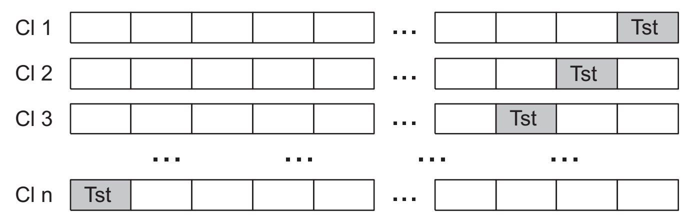

Fig. 14. The *n*-fold cross-validation procedure.

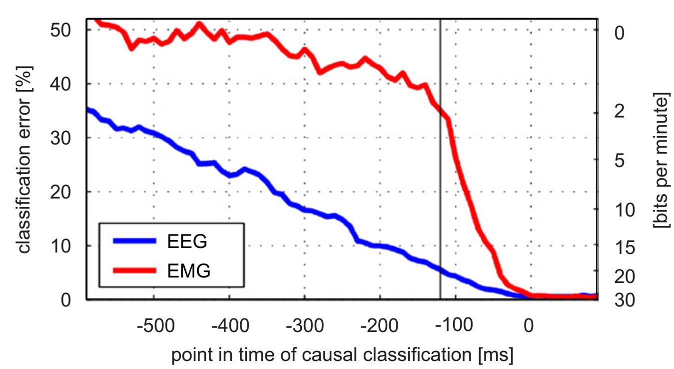

Fig. 15. Classification errors based on EEG (brain activity) vs. EMG (muscles activity) estimated by the 10×10-fold cross-validation procedure.

4. Results

To enable the classifier training, we initially let the user execute or imagine the required movement repeatedly. For real movements, which can be monitored, the user may perform tasks "self-paced". For imagined movements, or in paralyzed patients, the lateralization of each action (left/right) is queried by an auditory and/or visual cue. We extract training samples, preprocess each as described in Sections 3.3 and 3.4, calculate a set of optimal classifiers on a selection of 90% of the markers and test each on remaining 10% as it is described in Section 3.5. This procedure is repeated 10 times with all non-overlapping test-sets, which is called 10-fold cross-validation, cf. Fig. 14. In a 10×10-fold cross-validation the whole procedure is repeated 10 times with random foldings of the data set.

By calculating means of training and test errors, we obtain a measure for effectiveness of a particular classifier model. A test error essentially higher than the training error would indicate that the model is too complex for the given data, such that the risk of over-training is high due to bad generalization ability. Notably, test errors of the cross-validation procedure depend on the choice of the delay time t_d in the pre-processing procedure. Obviously classification is ambiguous for large values of t_d and mostly correct for $t_d = 0$. Fig. 15 shows the cross-validation test-error of classification of EEG single trials as a function of t_d for a single subject performing in a self-paced experiment with 30 taps/min.

The right ordinate enumerates the theoretical information transfer rate in bits per minute that can be extracted from the classification results. Compared to the errors of classification based on EMG (upper curve), which reflects the muscle activity in the forearms, the EEG approach yields superior classification results which become feasible already 120 ms prior to the actual movement execution. The EEG-based classification procedure retains its higher performance, as classifications obtained after the hit marker is presented are not interesting any more. This phenomenon is neurophysiologically evident, because the decision about lateralization of the movement has to be met in the brain firstly, followed by the preparation of cortical neurons and emission of the command down to the spinal cord, peripheral nerves and to the effector muscles spending at least 60–80 ms.

4.1. Feedback scenario "Jumping-Cross"

Initially we implemented a very simple visual bio-feedback application to provide the user with a first feeling of her/his intentions: a thick black cross is moving over a full-screened window containing a thin static fixation cross in the center and two target fields (dark-red and dark-green—indicating left-hand and right-hand movements, respectively). The ordinate position of the "jumping-cross" reflects the normalized decision of the movement detection classifier ("up" indicating action vs. "down" indicating rest), i.e., the cross jumps into the upper half of the screen on upcoming action. The abscissa position provides the natural mapping of the discrimination classifier result (left vs. right). The "jumping-cross" trails a history tail of 4 points (data drawn at 40 ms intervals). The single action trial is indicated as completed, when (i) the screen freezes on occurrence of an event marker, i.e., after an actual movement is performed, and when (ii) the corresponding lateralization field, the cross is actually located in, is highlighted. Fig. 16 illustrates a typical left and right event.

A series of single trials acquired over the whole experiment (here: 64 left and 64 right trials) may be represented in an instructive summary plot, cf. Fig. 17. Here, crosses were replaced, for clarity; by bold dots and the history tails are painted bold for the three most recent periods and thin for another four preceding periods. The axes represent the classification results of the discrimination and detection classifiers, respectively. It can be recognized at a single glance, that the majority of trials have been classified correctly.

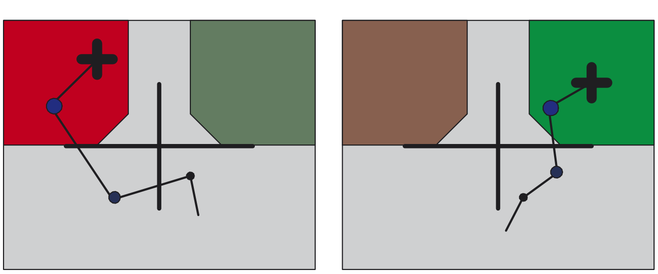

Fig. 16. Feedback scenario "Jumping-Cross" (typical left and right trials) with a 4-periods history tail.

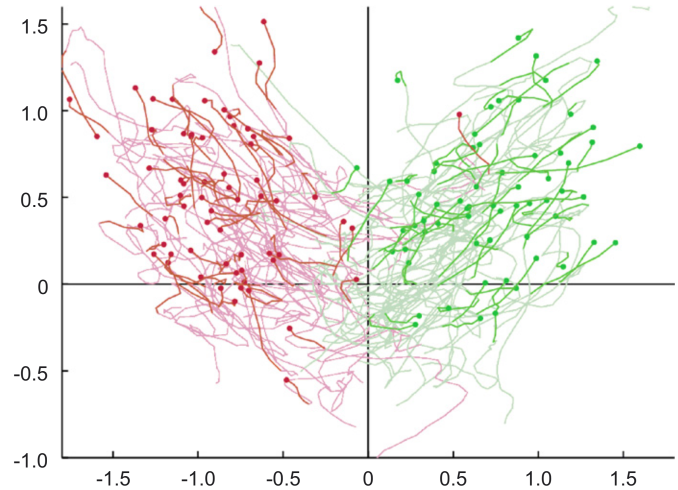

Fig. 17. Accumulated feedback trials (64 left and 64 right trials).

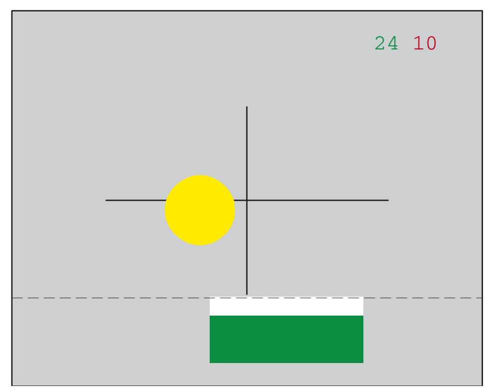

Fig. 18. Feedback scenario "Brain-Pong".

4.2. Feedback scenario "Brain-Pong"

In following experimental sessions, we introduced a simple discovery scenario based on a well-known game of Tele-Tennis. Set-up for a single-player, it is similar to the "Ping Pong" video game, cf. Fig. 18. A yellow ball is moving continuously over the screen in a certain direction, being bounced from the two lateral sides and the upper border of the screen. There is a movable bar (racket) at the bottom of the screen, which can be controlled by the subject's intentions using several strategies. We describe these in detail in Section 4.2.1.

Several subjects who used the BBCI system to play "Brain-Pong" reported several long phases with many successive successful trials. This provided them with the feeling that the racket was becoming integrated as a part of their own body and that no particular effort was required to maintain control. Moreover, it was reported that in successful phases, performance improved even more, whereas in failure phases filled with mismatching trials, performance dropped drastically. These observations are also evident from the neurological and machine-learning point of view. Since the user is not put under pressure during training sessions, she/he generates ordinary brain patterns that are fed into the learning machine. However, during application sessions with feedback, the user may become greedy and at some point generate different brain patterns induced by an additional effort to re-seize control over the feedback. To conclude, the user puts her/himself in a conflicting situation by applying more effort to gain control; the effort induces an immediate change in the brain pattern feature space, spanned by the training data and thus recognizable by the classifier, which results even more in losing control. "Brain Gamers" further report that when control performance worsens significantly (subjectively measured), simply adopting a relaxed state or indifferent attitude to the game helps to re-gain control over the machine.

4.2.1. Control strategies

Basically, we have implemented two different control strategies for the racket, while both appear appropriate in this scenario; in other applications one might be preferred over the other.

In the "stepwise displacement" strategy the racket is moved by a fixed displacement step (e.g., defined as percentage of the window width) into the direction indicated by the class label (left or right) if one particular command class is recognized for at least one CAT duration. The racket remains stationary if a "rest" command is detected (a stable signal for at least the CAT duration) or if no stable signal is present (if combined classifier result indicates more than one class label within a single CAT duration). Each step is followed by a relaxation period (CRT), which, for this control strategy, is set just slightly longer than CAT. Thus, the racket could be moved into the same direction by more than one step, with the minimal inter-step interval given by CRT + 1.

Notably, although the Lateralized Readiness Potential (LRP) can indicate the preparation for one particular movement, a series of movements (and movement repetitions in particular) need not necessarily be linked with LRPs of the same strength for every single movement; rather, the LRP might index primarily the start of the whole series, invoking subcortico-cortical routines for the execution of the repeated actions. This points to a potential limitation of the "stepwise displacement" strategy: if a fast racket transition from one side of the screen to the other is required, the user has to emit a series of identical commands. The identification of optimal EEG correlates for such a hyper-command will require further neurological studies.

A second control strategy utilizes a "graded displacement" code which exploits the strength of the recognized command signal, e.g., a measure of BP amplitude, instead of just the command emission time point identified by the combiner. From its initial location at the screen center, the racket can be deflected laterally (outward), but, as it is attached to an imaginary spring, it will be returned to its initial point (inward) whenever the fuzzy values of neither the "left" nor the "right" classes are significantly high. This control strategy has only a virtual "rest"-class for which fuzzy value may be calculated from the combination of the results of the "left"- and "right"-class fuzzy values. The outward racket deflections are calculated each time a new result data block is received from the classifiers, i.e., at a frequency of 25 Hz. Each deflection is proportional to the difference between the momentary graded values of the two action classes if and only if the graded value of the virtual "rest"-class is below a certain (usually low) threshold; otherwise, it is set to zero, such that the racket is almost always on the move. The value of the "rest"-class threshold controls the trigger sensitivity for the displacement activation and can be adjusted, together with the constant of proportionality for the racket outward deflection, depending on the individual user's experience and demand.

4.3. Feedback scenario "Pacman"

Finally, the well-known Pacman video game has been adapted to serve as bio-feedback. The idea is to combine the information, available from the "jumping-cross" feedback with an aim-gain inventively in a discovery application. A random labyrinth is generated in a full-screened window, which has exactly one shortest way (without detours) from the entry (in the left wall) to the exit (in the right wall). This path is marked with grey track marks. The player may also decide to run the Pacman through the rest of the labyrinth, e.g., to receive additional credits for harvesting some apples.

As control strategy we use the following approach: The Pacman makes one step each 1.5–2 s and moves always straight ahead until it reaches a wall or a right- or left-turn command is received. The direction the Pacman is intended to make in the next step is pointed by its yellow nose. When the system recognizes a turn-command for at least one CAT duration, Pacman turns its head indicating the recognition of the command and takes the next crossing possibility in the maze. After a turn command is acknowledged, the Pacman does not accept any further commands for at least CRT. The simulation is finished when the Pacman reaches the exit of the labyrinth, cf. Fig. 19.

A healthy subject will be able to navigate the Pacman through the presented labyrinth within 40 s (20 steps, each of 2 s) using a conventional keyboard or a mouse. Using brain control it takes considerably longer, however, the "fun-factor" of navigating just by intentions of the own brain turned out to be very appealing. Moreover, it is highly interesting that when immersed into the BCI-game scenario the user has sometimes the feeling that the Pacman moves in the correct direction though the user was consciously not aware of his decision, sometimes consciously not even ready for a decision.

4.4. Feedback scenario "Virtual Arm"

The "Virtual Arm" feedback scenario is based on a Virtual Reality (VR) platform X-Rooms (www.x-rooms.de).

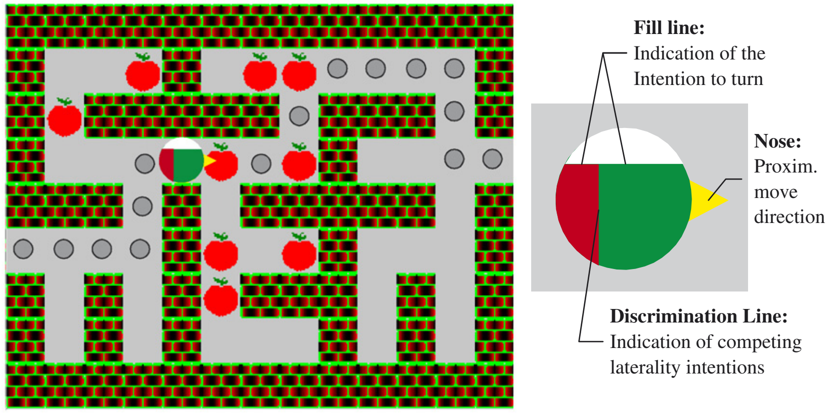

Fig. 19. Feedback scenario "Pacman" and the construction of Pacman's head.

The user is instructed to control a part of the body that may be absent and that is displayed on a computer screen. This feedback application still remains an open research field that requires prior solving of many neurological, technical and fundamental research problems, as well as design and conduction of further experiments with patients.

During the training session the user is instructed to perform imagined movements of the arm, e.g., bending it at the proximal (shoulder or elbow) and distal (hand or fingers) joints, which are triggered by an external query. During the application session the user is presented with a black full-screen window containing an image of a human arm. The BBCI is capable of recognizing the two spatio-temporal brain patterns as belonging to two different classes. The proximal joint flexion action is implemented by the up and down movement of the entire arm, i.e., by bending it in the shoulder or elbow joint. The distal joint flexion actions then are implemented by the hand closure and opening movement, i.e., by finger movements, cf. Fig. 20.

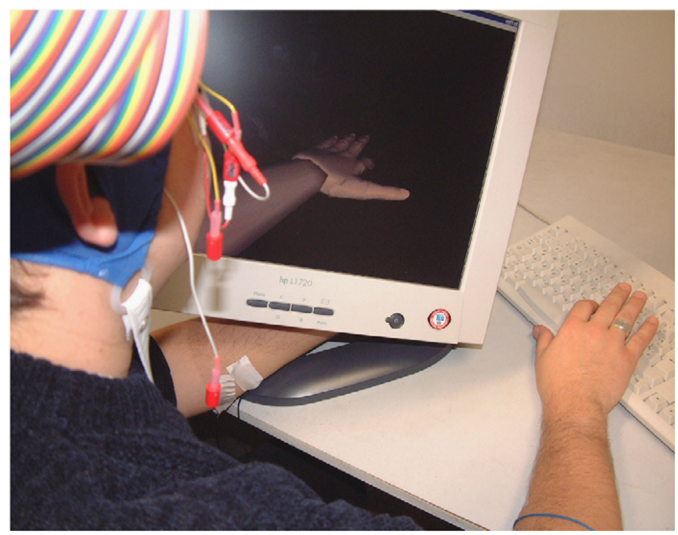

Fig. 20. Feedback scenario "Virtual Arm".

A future vision is that a patient not capable of controlling her/his own limb (in this case an arm) could then gain control over a virtual limb in a natural way. As a result, if the patient's Central Nervous System (CNS) is still intact and capable of generating the appropriate control commands for bending and grasping, and if she/he is still able to feel or imagine an amputated limb, the BBCI system would serve as a bridge between the command emission unit and the executing extremity, bypassing all the intermediate interfacing elements such as spinal cord, peripheral nerves and muscles.

For users with absent limbs, prostheses can be replaced by intelligent robotic mechanisms that can be controlled by the user's brain signals encoded as emitted commands. Furthermore, a Virtual Arm that is physically located at a remote place, but connected to the BBCI user via the Internet can be controlled easily by generating brain activity patterns independent from those of a real arm movement. This could provide the operator with a "third limb" that would be able to perform some simple, but important tasks in some difficult accessible environment. Orthosis can be employed for users whose limbs are present, yet who have no control of these limbs due to a neuromuscular disease. In this case, if the executive muscles of the limb are still intact and usable to implement movements, an electro-stimulator sleeve (e.g., an arm or wrist band) is employed to process the user's brain signals encoded as control commands. The sleeve transforms control signals from the Virtual Arm interface into an electrical stimulation of limb muscles, such that the imagination of a certain movement yields the execution of the desired movement in the limb. The underlying intent of this feedback scenario was to investigate a virtual version of such prosthesis and to define the control procedure for the orthosis. The technical realization of such a prototype is a challenge to be met by experts in the field of robotics and prosthesis development and research.

Experiments with patients are still to be conducted within the scope of future BBCI research.

5. Conclusion and discussion

BCIs have traditionally been conceived and used in assistance systems for the disabled, e.g., Wolpaw et al. (1991, 2002) and Birbaumer et al. (1999) and many more. We have shown in this contribution that our BBCI discovers also the interesting path towards interactive applications; exemplified here as gaming and robotic arm control.

The field of HCI research is expanding to encompass brain signal-based communication and interaction. That trend had its onset when, among other factors, BCIs introduced a new technique for reliably decoding brain signals and converting these into control commands, which can be used for appealing interaction. Currently, the two most prominent and promising paths of BBCI application are rehabilitation, discovery and gaming, although further application fields are conceivable, such as the monitoring of the mental state of a patient or vehicle driver. The latter could be used to prevent overfatigue of truck drivers and guard against accidents. The bio-feedback signals introduced in this contribution hold potentials for further optimization, but already now allow a user who has taken a "cold-start" to explore and discover her/his individual possibilities in using the new communication channel. Concerning rehabilitation the most promising perspectives, e.g., for quadriplegic patients, are the intuitive use of mental motor commands to trigger goal-directed actions of mechanical devices, such as a motorized wheel-chair, or to use a "mental keyboard" for typing messages.

In general, the question surrounding an ideal bio-feedback signal for BBCI will find different answers appropriate for each new application. However, we propose that bio-feedback in an exciting gaming scenario (Pacman), or within a native VR environment (Virtual Arm), can be realized more naturally and thus more successfully. Eventually such bio-feedback can enable the user to adapt to the classification engine and vice versa; the classification engine might find it easier to classify correctly in the course of mutual adaptation (Krepki, 2004).

While most BCIs (except VEP or P300-based) require extensive training (>200 h) from their users, it is one distinctive feature of the BBCI that it employs advanced signal processing and machine learning technology for training the computer rather than the human subject, such that the user can start "communicating" without extensive prior training. There are several aspects for further improvement of BBCI: so far we have used a paradigm, where the user actually implements or imagines the accomplishment of a movement, i.e., typing with the left or right index or pinky fingers. In ongoing research we transfer this paradigm to assistance systems where a disabled person still has movement intentions and their respective neural correlate, but no means for an actual movement.

Another issue with pioneering appeal is the thrilling possibility that, because the BBCI bypasses the conduction delays from brain to muscles, it could speed up the initiation of actions in competitive, dual-player scenarios or applications that require ultra-fast actions, like emergency braking. However, the experimental design of this kind of application must differ to some extent from those performed previously and presented within the scope of this work. The conceptual scheme, design and implementation of such competitive scenarios as a feedback application will require considerable innovation.

Let us finally discuss how much information we can expect to transmit in such a new BCI channel. Invasive technologies, like those proposed in Nicolelis and Chapin (2002) can achieve bit-rates that are high enough for, e.g., an online 3-D robot control (as discussed earlier), but require hundreds of microelectrodes implanted into the brain's cortex, which is an unlikely condition for healthy subjects. For non-invasive techniques our own earlier studies have shown that in a pseudo-online idealized evaluation (i.e., data are recorded and analysed later as if online) record bit-rates of up to 50 bits per minute are possible (Blankertz et al., 2003). Our recent experiments have shown that even higher transfer-bit rates can be achieved if several data processing models are combined (Dornhege et al., 2004a, b). In spelling task experiments conducted by Wolpaw et al. (1991), Pfurtscheller et al. (1993) and Birbaumer et al. (1999) that are truly online with bio-feedback, single subjects can reach a level of 2–3 letters/min. A recent BBCI study even achieves 37 bits/min in a real-time feedback set-up (Blankertz et al., 2006). At first sight, this might appear rather slow for a communication device, as other communication devices, e.g., a computer mouse can achieve 300–350 bits/min (MacKenzie, 1991). Yet, one should realize that a BCI communication channel is largely independent of other channels and offers a unique feature of ultra-fast action emissions for each single reaction trial.

Finally, there is a strong agreement that BCI research will seek to develop new and more natural feedback modi and feedback applications rather than re-developing and adapting well-known applications to be controlled by brain signals. The reason for that is because the latter were designed to rely on classical communication and control strategies. Moreover, the field of human–computer interaction will be increasingly in demand and will be called on, in particular, to provide new techniques and communication protocols that can serve as a basis for BCI-based communication. In conclusion, we discussed state-of-the-art BCI research and presented recent results that could be achieved by providing interactive feedback to the user. BCIs are able to open up new vistas for exploring own brain skills and discovering new ways in human–computer communication.

Acknowledgements

Many thanks to our colleagues at the Fraunhofer-FIRST: Guido Dornhege and Christin Schäfer; and at the UKBF: Florian Losch and Volker Kunzmann who helped to develop the system described here. Partial funding by the BMBF is gratefully acknowledged.

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