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Clinical application of an EEG-based brain–computer interface: a case study in a patient with severe motor impairment

C. Neuper[a,b,*], G.R. Müller[b], A. Kübler[c], N. Birbaumer[c,d], G. Pfurtscheller[a,b]

[a]Ludwig–Boltzmann Institute for Medical Informatics and Neuroinformatics, University of Technology Graz, Graz, Austria
[b]Department of Medical Informatics, Institute of Biomedical Engineering, University of Technology Graz, Inffeldgasse 16a/II, A-8010 Graz, Austria
[c]Institute of Medical Psychology and Behavioral Neurobiology, University of Tübingen, Tubingen, Germany
[d]Center for Cognitive Neuroscience, University of Trento, Trento, Italy

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Abstract

Objective: This case study describes how a completely paralyzed patient, diagnosed with severe cerebral palsy, was trained over a period of several months to use an electroencephalography (EEG)-based brain–computer interface (BCI) for verbal communication.

Methods: EEG feedback training was performed in the patient's home (clinic), supervised from a distant laboratory with the help of a 'telemonitoring system'. Online feedback computation was based on single-trial analysis and classification of specific band power features of the spontaneous EEG. Task-related changes in brain oscillations over the course of training steps was investigated by quantifying time–frequency maps of event-related (de-)synchronization (ERD/ERS).

Results: The patient learned to 'produce' two distinct EEG patterns, beta band ERD during movement imagery vs. no ERD during relaxing, and to use this for BCI-controlled spelling. Significant learning progress was found as a function of training session, resulting in an average accuracy level of 70% (correct responses) for letter selection. 'Copy spelling' was performed with a rate of approximately one letter per min.

Conclusions: The proposed BCI training procedure, based on electroencephalogram (EEG) biofeedback and concomitant adaptation of feature extraction and classification, may improve actual levels of communication ability in locked-in patients. 'Telemonitoring-assisted' BCI training facilitates clinical application in a larger number of patients.
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Keywords: Brain–computer interface; Electroencephalogram; Biofeedback; Event-related desynchronization; Sensorimotor cortex; Telemonitoring system

1. Introduction

Patients diagnosed with a neurological disease, such as amyotrophic lateral sclerosis or cerebral palsy, may be severely physically impaired or even completely paralyzed. Such patients are referred to as being 'locked-in': a cognitively intact brain is locked in a paralyzed body (Allen, 1993). In the past years, it has been shown that it is possible to recognize distinct mental processes from the online electroencephalogram (EEG) (see, for example, Kalcher et al., 1996; Pfurtscheller et al., 1997; Anderson et al., 1998; Obermaier et al., 2001). By associating certain EEG changes to simple commands, it is possible to develop a new communication device for completely paralyzed patients. In such a case, the electrical brain activity is used to control a computer, resulting in an alternative communication channel, which is usually called a 'brain–computer interface' (BCI; Vidal, 1973; Wolpaw et al., 1991).

In general, research on EEG-based communication depends on two convergent approaches. The first is the ability of individual patients to learn to control their brain activity. Through appropriate training, it is possible to generate certain EEG patterns which can be used, for example, to control cursor movements (Wolpaw et al., 1991, 1997) or to select letters or words on a computer monitor (Birbaumer et al., 1999; Kübler et al., 1999). This approach implies a large training effort for the patient since he or she must acquire self-control over a certain EEG signal, such as the sensorimotor mu rhythm (Wolpaw et al., 1991) or slow cortical potentials (Kübler et al., 1999). The basic principles of EEG biofeedback and its use in a brain–computer

* Corresponding author. Department of Medical Informatics, Institute of Biomedical Engineering, University of Technology Graz, Inffeldgasse 16a/II, A-8010 Graz, Austria. Tel: +43-316-873-5317; fax: +43-316-873-5349.

E-mail address: neuper@tugraz.at (C. Neuper).

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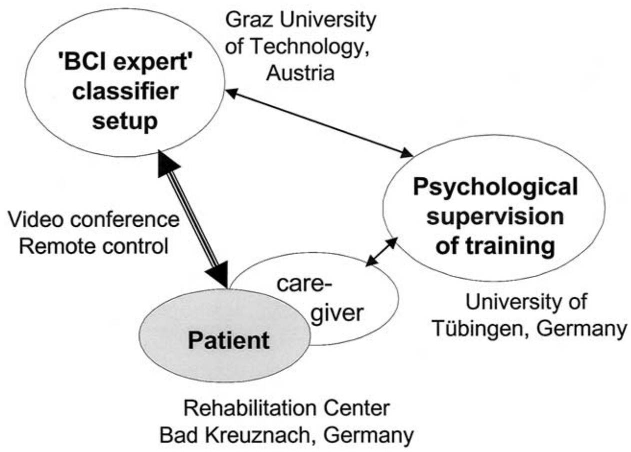

Fig. 1. Schematic display of the BCI training management at different geographical locations. Direct work with the patient took place at the Rehabilitation Center, Bad Kreuznach, Germany; regular psychological support and supervision of the communication training was supported by N. Birbaumer's group (University of Tübingen, Germany); the implementation of the BCI training was performed by the laboratory of G. Pfurtscheller (Technical University Graz, Austria). 'Telemonitoring' was realized via video conference and remote control connection between Bad Kreuznach and Graz.

communication device for paralyzed patients have been described previously (Birbaumer et al., 1981; Kübler et al., 2001b).

The second approach is the rapidly increasing capability of online EEG processing systems that provide the possibility to develop subject-specific classifiers to recognize different cognitive processes online from EEG signals (Pfurtscheller et al., 1997; Anderson et al., 1998; Guger et al., 2001; Obermaier et al., 2001). Various types of BCI systems emphasizing the 'machine learning idea' have been developed so far. Some of them are based on event-related potentials (Farwell and Donchin, 1988; Middendorf et al., 2000), others, such as the 'Graz-BCI' used in this study, focus on recognition of EEG frequency patterns (Pfurtscheller and Neuper, 2001). Most of this research work, however, was performed on healthy volunteers. Hence, there is a need to evaluate the performance and acceptance of such classifier-based BCI systems in severely paralyzed patients.

Previous studies with the Graz-BCI system investigated motor imagery as a control strategy to achieve distinct oscillatory EEG patterns, using various methods of EEG data preprocessing and classification. In a number of able-bodied participants (see e.g., Kalcher et al., 1996; Guger et al., 2000) as well as in a patient with high-level spinal cord injury (Pfurtscheller et al., 2000), it has been shown that it is possible to satisfactorily identify two to three motor imagery tasks. Two types of oscillations are relevant for the classification, the Rolandic mu rhythm in the range 7–13 Hz (Kuhlman, 1978) and the central beta rhythm above 13 Hz, both originating in the sensorimotor cortex (Salmelin et al., 1995; Crone et al., 1998). Both can be modified not only by execution of a limb movement, but also by imagination of specific movements (Pfurtscheller et al., 1997; Neuper and Pfurtscheller, 1999).

An open issue remained, however, whether or not this type of mental strategy can also be applied by patients suffering from a neurological disease affecting various functional components of the central nervous system and compromising the ability to communicate. The main goal of this paper was to describe how a patient diagnosed with infantile cerebral paresis was trained over a period of several months to use the Graz-BCI for verbal communication. A sophisticated feedback training was applied to enable him to develop an individual strategy for self-control of EEG changes. Considering the complexity of brain oscillations during mental processes, the generation of appropriate EEG feedback required dynamic adjustment of the classifier and of the feedback parameters. An important prerequisite to realize this classifier-based BCI training in a clinical setting was the implementation of a 'telemonitoring system' (Müller et al., 2001). This novel technical concept permitted the responsible scientists ('BCI expert') in the laboratory to supervise the training at the patient's home supported by an instructed caregiver.

2. Methods

2.1. Patient

The male patient, 32 years old, was diagnosed with cerebral palsy. He suffered from a severe spastic form of tetraparesis and had lost the ability to speak. Residual muscle activity of the upper right extremity enabled him, assisted by a caregiver, to slowly move his right arm to select letters from a small keyboard for communication purposes. However, during the increasingly frequent periods of severe spasticity, the ability to communicate was lost altogether.

2.2. Background

The BCI training was conducted at a clinic for Assisted Communications (Rehabilitation Center Bethesda kreuznacher diakonie, Germany) where the patient lived and was cared for permanently.

At the beginning of this cooperative project (Fig. 1), one important obstacle was the large geographical distance between the hospital and the technical laboratory. In general, when using a complex, classifier-based BCI, there is need of a qualified person familiar with the technical parts of the system and being in charge of the patient's training. With implementation of a 'telemonitoring system', it was possible to control and supervise the training procedure directly from a distant laboratory. Data acquisition, including the application of electrodes, amplifier set up and data storage, was carried out by an instructed caregiver. Via 'remote control', the BCI engineer had direct access to

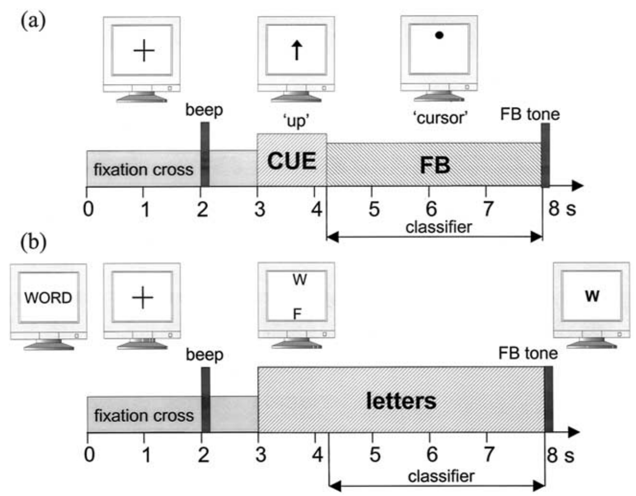

Fig. 2. Timing of (a) cue-guided training and (b) letter selection. (a) At 3 s, the cue stimulus was displayed as an arrow pointing to the target direction (up/down). The patient's task was to move the 'cursor' (dot) in the indicated direction during the following 4 s-period. Correct reactions were reinforced by an auditory feedback signal ('FB tone') at 8 s. (b) Before the beginning of the trial, a word was presented. At 3 s, two letters were displayed. The patient's task was to select the target letter presented either at the top or the bottom of the monitor. Correctly selected letters were shown after the end of the trial.

the system used by the patient (Guger et al., 2001). This facilitated repeated adjustments of the paradigm and of feedback computation according to the individual's performance. A video conference system enabled a visual and auditory connection and therefore, direct instructions to the patient as well as supervision of the patient's and the care person's behavior. The technical concept of the telemonitoring-assisted BCI has been described in detail elsewhere (Müller et al., 2003).

The results reported here refer to a time period of 22 weeks, where regular telemonitoring-assisted training of 2 days per week was performed. At the beginning of this training period, the classification performance was at random level, although the patient had some previous experiences with the task. Because the telemonitoring system had been installed after a relatively long pause of several months, it was decided to restart with an individually determined step-by-step procedure.

2.3. Standard Graz-BCI paradigm

During the training, the patient watched a computer monitor 150 cm in front of him. According to the standard paradigm for the discrimination of two mental states (for details see Pfurtscheller and Neuper, 2001), each trial started with the presentation of a fixation cross at the center of the monitor, followed by a short warning tone ('beep') (Fig. 2a). Depending on the following visual cue stimulus, displayed for 1.25 s, the patient was instructed to imagine a predefined motor movement.

Two different types of feedback were used: (i) discrete/delayed and (ii) continuous feedback. Discrete feedback consisted of a visual or auditory signal presented near the end of the trial (e.g. at 8 s). The signal indicated whether or not the classifier was able to recognize the imagination-related EEG characteristics. In case of continuous feedback, the patient's task was to control online cursor movement (e.g. displayed as a 1.5 cm dot moving up vs. down) for a 4 s period, depending on the cue stimulus (e.g. arrow pointing up vs. down).

In this study, each session consisted of 4 runs of 20 trials each (10 'up' and 10 'down' trials) and lasted for about 15 min. On a regular training day, 3–5 sessions, lasting in total from 1.5 to 2 h, were performed.

2.4. EEG recordings and apparatus

The EEG signal used for classification or feedback, respectively, was recorded with one bipolar channel from the left sensorimotor cortex: one electrode was placed 2.5 cm anterior and the other 2.5 cm posterior to the electrode position C3. A further recording channel, based on two electrodes located medially and laterally to C3, respectively, was used for data control. The ground electrode was placed on the forehead. The EEG signal was filtered between 5 and 30 Hz (using an additional 50 Hz notch filter) and sampled at 128 Hz. To rule out the possible involvement of EMG artifact due, for example, to cranial muscle activation, additional recording sessions were conducted using a broader frequency range up to 70 Hz. These additional control sessions were performed later in training, to rule out the possibility that the patient was using EMG rather than EEG activity to control the device.

A recently developed BCI system was used running in real-time under Windows with a 4-channel EEG amplifier (Guger et al., 2001). The installation of this system, based on a rapid prototyping environment, included a software package that supported the real-time implementation of different EEG parameter estimation and classification algorithms. This BCI system was equipped with a remote control feature that allowed direct access over an analog dial up, LAN or Internet connection from a different location.

2.5. Data processing and online feedback

To generate the feedback based on oscillatory components of the ongoing EEG, we used two approaches: (i) direct band power feedback and (ii) feedback calculated by a linear discriminant classifier, which was developed to discriminate between two brain states. In both cases, data analyses were based on the calculation of the band power in predefined subject-specific frequency bands (Pfurtscheller et al., 1997). To estimate the band power, data were first digitally band pass filtered (Butterworth, order 5), then each sample squared and then averaged across consecutive samples.

For (i) the band power estimates were continuously extracted from a moving 4 s epoch (i.e. averaging over 512 samples) recorded during patient's imagery and displayed as a dot moving up (band power increase) vs. down (band power decrease). The discrete feedback stimulus at the end of the trial was based on a comparison between the band power determined at 8 s (mean band power of the interval 4–8 s) and the baseline band power (mean band power of the interval 0–4 s). To ascertain a band power decrease and increase, respectively, two thresholds defining the required deviation from the baseline had been introduced. These thresholds were computed from a data set obtained during 'free training' (step 2, described below), where the patient was either instructed to relax or to imagine performing movements, respectively, for a period of 2 min. Hence, an empirically determined, fixed interval was used for the dynamically computed reference power values.

The classifier-based feedback (ii) implied the calculation of the band power estimates in 1 s intervals. These band power features were subjected to linear discriminant analysis (LDA) and classified into two classes according to the output of the discriminant (Guger et al., 2001). With both methods it was possible to provide feedback by either a continuously moving feedback spot or a discrete feedback signal at the end of each trial.

To obtain a more detailed view of task-related EEG changes and classification performance, additional off-line data analysis was performed for each session. This included, for example, the calculation of the time course of classification accuracy across the trial as well as separate analysis of 'up' and 'down' trials. 'Off-line accuracy', based on band power features, was determined by using a 10 by 10-fold cross validation of a linear discriminant, calculated in 0.5 s intervals. This procedure is described in detail elsewhere (Guger et al., 2001).

For the two classes of trials (up/down) or mental strategies, respectively, event-related (de-) synchronization (ERD/ERS; Pfurtscheller and Lopes da Silva, 1999) was investigated by calculating power spectra and time–frequency maps. The latter method, described in detail elsewhere (Graimann et al., 2002), provided plots of significant event-related power decrease (ERD) and power increase (ERS) in predefined frequency bands within the entire frequency range of interest. Twenty overlapping frequency bands in the range between 5 and 32 Hz were analyzed in parallel over the time course of the trial. Averaging over 16 consecutive band power values resulted in a time resolution of 125 ms. The band power in each time–frequency segment was compared to the mean band power in the reference interval (0.5–1.5 s). The resulting ERD/ERS values were tested for significance by applying the t-percentile bootstrap algorithm (Davisison and Hinkley, 1997). Only significant ERD/ERS values ($P < 0.05$) were displayed in the map.

2.6. Stepwise training procedure

Based on previous experiences with patients who acquired control over their slow cortical potentials and were finally able to select letters or words in a Language Support Program (Kübler et al., 2001b), we developed the following training schedule, where we considered two aspects: on the one hand, dividing the learning process into small steps of mastering for the patient, and on the other hand, the search for the best suitable classifier to enhance the performance of the system.

Step 1: basic training: selection of the most efficient imagination strategy

In the first sessions, when the patient was confronted with the BCI training, EEG data were collected using the time schedule of the standard BCI paradigm (as described above). The patient was instructed to perform sequentially various mental imagination tasks in response to the cue stimulus. Since the most efficient motor imagery strategies vary from individual to individual (Obermaier et al., 2001), we had to find the most suitable approach for this patient. This denotes a search for those two mental imaginations that can produce distinct and reliable EEG patterns. No feedback was provided at this stage.

As a result of the off-line analyses, the best discrimination was achieved for imagination of a right hand movement vs. mental relaxation. EEG power spectra and ERD/ERS time–frequency maps (see Fig. 4, described below) revealed a significant desynchronization (ERD) of alpha and beta frequency components during movement-imagination. However, an ERD was also present in the EEG during relaxation trials, in which the patient was told to relax and to think of nothing in particular. Hence, mere presentation of a cue stimulus elicited a task-unspecific, attention-related ERD in a relatively broad frequency range. The discriminating feature was a prominent, long-lasting desynchronization of higher beta band (above 20 Hz) components during imagination of right-hand movement, which was not visible, to that extent, during other imagination tasks or relax-instruction. This observation led us to utilize upper beta band (20–30 Hz) activity for BCI control. The idea was to train the patient, on the one hand, to suppress these specific EEG components (reduce band power) by motor imagery ('down' trials) and, on the other hand, to enhance spontaneous beta frequencies that occur in the course of normal brain function ('up' trials).

Step 2: free training

In order to improve the ability to discriminate the two mental states, the following feedback training was performed. For a time period of 2 min, the band power (20–30 Hz) was continuously averaged over 4 s and displayed on the screen as a moving feedback dot ('cursor'). The patient was advised that, imagination of right hand movement, moved the cursor downward. Relaxation, in contrast, either moved the cursor upward or it remained in the center of the screen. Before the beginning of such a feedback period, a verbal instruction was given, such as, to try to move the cursor to the upper or lower part of the screen, respectively.

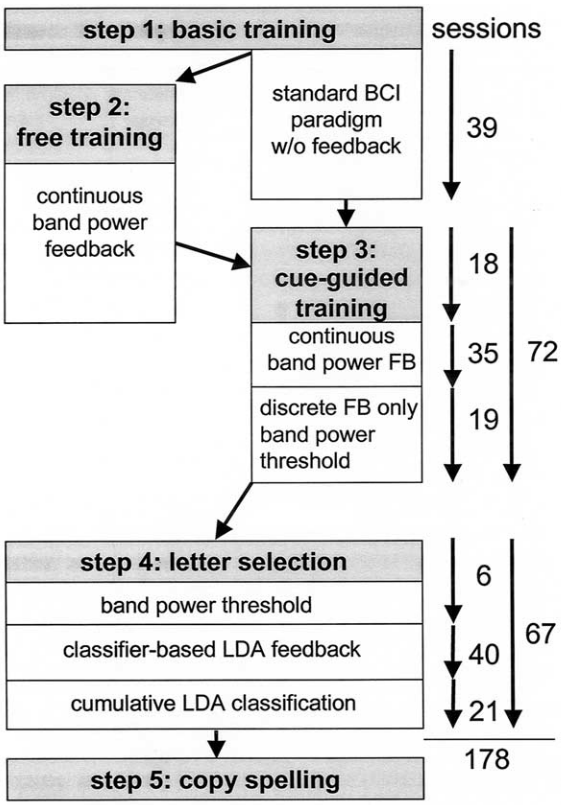

Fig. 3. Diagram of training steps (as described in the text, Section 2.6) and corresponding number of performed sessions (right side).

This free training (without time schedule of a trial) revealed that it was easier for the patient to move the feedback signal downward (reduce band power) and keep it there for some seconds than to hold it in a middle or upper position (increase band power). Considering the general ERD pattern in the initial data sets, obtained without any feedback, this effect was not unexpected. Thus, the main goal of this free training was to support the patient in finding a strategy to hold the cursor in a central or upper position or, in other words, to avoid band power suppression.

Step 3: cue-guided training

The next step was to use the time schedule of the standard BCI paradigm for the band power feedback training. At first, both continuous and discrete feedback was provided. Similar to the free training, the cursor was presented during the time period after cue presentation. Its position was based on the actual band power, computed over a 4 s time interval. For the final 'up' or 'down' decision, the position of the feedback signal at 8 s was compared to that at 4 s. It was determined whether the band power at 8 s exceeded the lower or upper threshold in the indicated direction. Whenever the patient succeeded in a band power change according to the cue (up/down), a feedback tone was presented. This means that only correct reactions (hits) were indicated. After each recording run (20 trials), the percentage number of correct responses was presented on the screen to inform the patient about the actual performance. After a number of sessions, the continuously shown feedback dot was omitted and, further on, only discrete feedback was provided at the end of the trial.

Step 4: letter selection task

The next step in training was to use the acquired ability to self-generate EEG patterns for letter selection. Instead of the cue stimulus (arrow pointing up/down), two letters were presented, one near the top, the other near the bottom of the monitor (Fig. 2b). The patient was instructed to select one by either relaxing or movement imagination, respectively. To select the upper letter, an increase in band power had to be produced by relaxing, whereas selection of the lower letter was achieved by motor imagery leading to band power decrease. At the beginning of letter selection training, a target letter (e.g. 'K') had to be selected in each trial, whereas the other letter was randomly chosen from the alphabet. Again, the percentage of correct selections was indicated for each run.

To overcome the problem that the fixed thresholds might become inappropriate over the course of sessions, a linear classification method was implemented to provide online feedback. Based on off-line analyses of data obtained during letter selection two beta frequency bands (16–20 Hz and 20–30 Hz) were selected as input features. At first, classification was performed at a certain time point at the end of the trial (e.g. at 8 s); further data analyses led us to include several time points (e.g. 5 time points within the time window 6–8 s) in the classification process (cumulative LDA classification). It should be mentioned that the implementation of a classifier-based selection process did not mean any change for the patient's task. It rather implicated an improvement of the ability of the system to recognize the self-generated EEG patterns.

Step 5: copy spelling: classifier-based communication

In the final step in this sequence of training paradigms, the patient was confronted with a modified version of the so-called 'Virtual Keyboard', described in detail elsewhere (Obermaier et al., 2003). His task was to copy words presented by the experimenter ('copy spelling'). The spelling involved the selection of a letter using successive steps of separation. Instead of single characters, a predefined set of letters, split into two equally sized subsets, was presented at the top and at the bottom of the monitor, respectively. When the patient achieved to select the subset, which contained the target letter, this subset was again split into two parts. This was continued until the patient selected the desired letter and, in a further step, confirmed this selection. The initial set of letters was successively increased, e.g., from 4 to 8 to 16 letters; this means that 3, 4, or 5 binary decisions, respectively, were at least necessary to select a particular letter and to confirm it. During the first weeks of training in copy spelling, only correct selections were accepted by the system, although false selections were

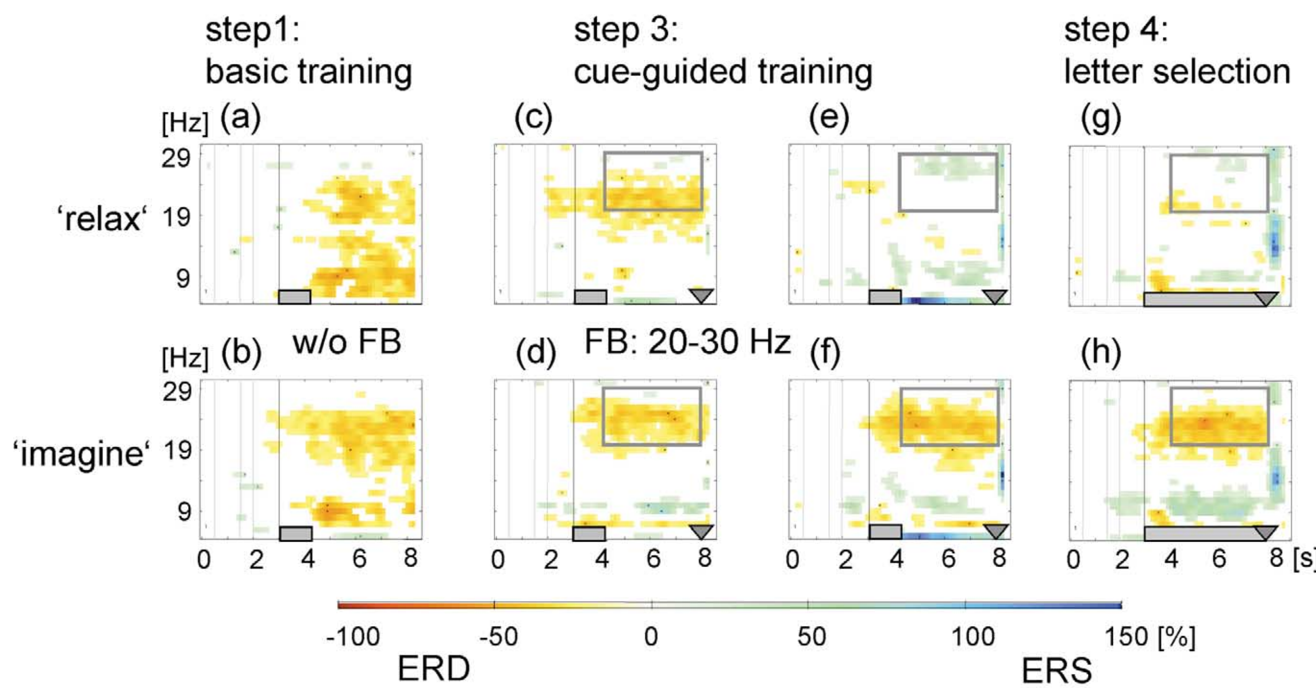

Fig. 4. Examples of time–frequency ERD/ERS maps from different phases of the training: basic training (a),(b), cue-guided training (c–f), and letter selection (g,h). 'Relaxation' trials (upper panels) and 'movement imagination' trials (lower panels) were averaged separately. Each map is based on 160 trials, recorded during 4 sessions of one training day. Only significant values of ERD (marked by yellow and red colors, maximum at 100%) and ERS (marked by green and blue colors, maximum at 150%) are displayed according to the color bar. Time resolution is 125 ms, 20 overlapping frequency bands between 5 and 32 Hz were analyzed in parallel. The horizontal bar (light gray) indicates cue/letter presentation, the gray triangle indicates the feedback signal. The feedback frequency band (20–30 Hz) and the time period where feedback was provided (4.25–8 s) are marked by a gray rectangle within the map.

measured for off-line analyses. This 'error ignoring' mode (Kübler et al., 2001b) was introduced to avoid the consequences of a wrong selection during training. Later, an additional selection step was introduced to enable the patient to delete a wrong letter and restart with the selection procedure (for more details of the spelling system used see Obermaier et al., 2003).

An overview of the different training steps involving both learning of the patient as well as adaptation of the system is depicted in Fig. 3. Free training (step 2) was always performed in parallel with specific BCI sessions; it constituted the first part of each training day, the second part comprised 3–4 sessions with the standard BCI paradigm (e.g. step 1). This training phase lasted until EEG power spectra and ERD/ERS maps revealed differences between the two classes of trials. To facilitate transfer from free to cue-guided training, both types of training were further combined for some sessions. First, cue stimuli were presented alternately in a predictable order. A randomized order, as usually used, was introduced after a few sessions. Analogously, letter selection was at first predictable (e.g. always letter 'K' as target letter). In a further step, the patient's task was to copy presented words. Each training day started with a session in which conditions were the same as in the terminal session of the previous training day. This was to ascertain previous performance.

3. Results

3.1. Feedback effects on ERD/ERS

To illustrate task-related changes in brain oscillations over the course of the training steps, representative ERD/ERS time–frequency maps during mental relaxing (upper panel) versus movement imagination (lower panel) are depicted in Fig. 4. Each map is based on 160 averaged trials (data of 4 sessions, recorded on one training day) and represents the activity in the range of 5–32 Hz over the entire trial (8.5/9 s). Only significant band power decrease (ERD, marked by yellow and red colors) and increase (ERS, marked by green and blue colors) is displayed according to the color bar.

Maps (a) and (b) represent the dynamic ERD/ERS patterns found at the beginning of the training where no feedback was provided (step 1). The patient had either to relax or imagine hand movements, as indicated by an arrow pointing upward or downward, respectively. In both tasks, a significant desynchronization (ERD) of alpha and beta frequency components were associated with presentation of the cue stimulus. Hence, presenting the task on the screen elicited task-unspecific, attention-related activation. The following maps (c–f) represent step 3, 'cue-guided training', with discrete band power feedback. Maps (c) and (d)

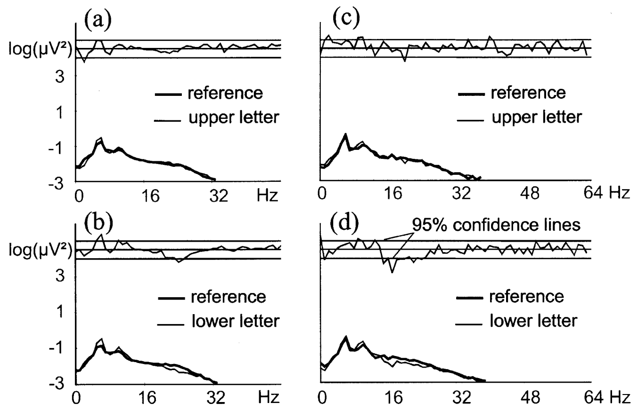

Fig. 5. Left side: Examples of power spectra recorded during 'up' (a) vs. 'down' trials (b) of one recording day (same data as displayed in Fig. 4g,h): superimposed logarithmic 1 s power spectra calculated in the reference period before the beep (thick line) and the imagination/selection period (thin line) during letter presentation as well as the difference between the two spectra with the 95% confidence intervals. Right side: examples of power spectra of a control session using amplifier filter settings of 5–70 Hz.

were obtained immediately after the free feedback training (step 2) was completed. As a result of the specific band power (20–30 Hz) feedback, hand movement imagery resulted in a clear-cut ERD in the beta frequency band. However, a beta band ERD was also found in the relaxation condition, though rather lower in frequency range. Therefore, it was an important progress when the patient, facing an arrow pointing upward, succeeded in relaxing without producing ERD (see maps e, f). In contrast to classifying differences of reactive beta frequencies, it was now possible to identify clearly different EEG patterns associated with the two classes of trials. These distinct EEG patterns, beta band ERD during movement imagery versus no ERD during relaxing, were further on used by the patient to select a target letter from the bottom versus top of the monitor, respectively (see maps g, h). The corresponding EEG power spectra are shown in Fig. 5 (left side), together with data from a follow-up control session performed 6 months after the training period described in this paper (right side).

The ERD/ERS maps demonstrate, moreover, that not only the preselected feedback frequency band, but also other frequency components may change concomitantly during training sessions. The most prominent effect is the disappearance of the alpha band ERD after the free feedback training (step 3), which is even replaced by an alpha ERS in later sessions (step 4, letter selection).

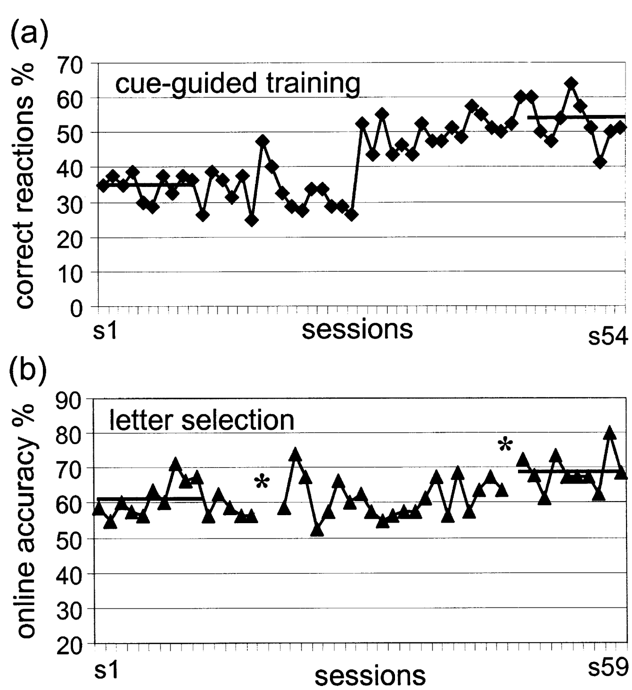

Fig. 6. Online performance as a function of sessions during cue-guided training (a) and letter selection (b). (a) Percentage of correct responses (threshold comparison) for 54 comparable, consecutive sessions. (b) Percentage of correct classifications (LDA with band power features) for 59 sessions. Each session consisted of 80 trials. The mean performance for the first 10 sessions and for the last 10 sessions is indicated, respectively. Missing data due to disturbances during sessions are marked (*).

3.2. Online performance and classification

To describe the performance over the entire training period, the online results of training sessions are shown as percentages of correct responses (Fig. 6). During the cue-guided training (a), determination of hits was based on a band power threshold comparison, whereas, later in training, during letter selection (b), a classification method was used to discriminate motor imagery vs. relaxation. Since the obtained performance estimates cannot be compared directly, the learning progress was evaluated separately for both training periods, based on direct band power feedback and classifier-based discrimination, respectively. Using the non-parametric Wilcoxon test for paired samples, we compared the first 10 consecutive sessions to the last 10 sessions within both training periods. Accuracy, in terms of the percentage of correct responses determined by band power threshold, increased significantly ($P = 0.005$) from 34.9% (SD = 3.4) to 53.5% (SD = 6.8) during cue-guided training. Analogously, the online accuracy during letter selection indicated a significant performance improvement ($P = 0.02$) from the first (61.6%, SD = 5.3) to the last 10 sessions (68.9%, SD = 5.4).

Separate analysis of 'up' and 'down' trials, respectively, is displayed in Fig. 7. The percentages of correct responses over a large number of consecutive sessions revealed a stable performance level for 'down' trials. This shows that the latter were easier to perform, at least in the initial phase of the cue-guided training. 'Up' trials, in contrast, showing low performance at the beginning, revealed a linear trend of increasing performance over sessions ($R^2 = 0.6$). Hence, increasing levels of overall performance were due to a substantial learning progress with regard to 'up' decisions. This is in line with the observation that the ability to suppress ERD by mental relaxation became stable during cue-guided training (see Fig. 4).

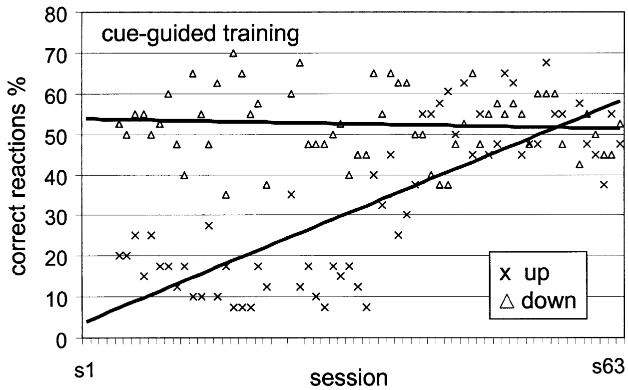

Fig. 7. Performance (percentage of correct responses) over consecutive sessions of cue-guided training, separately for 'up' (marked by ×) and 'down' trials (marked by △). Note that the indicated linear trends reveal a stable performance level for down-trials, in contrast to increasing performance over sessions in up-trials.

Classification accuracy was further analyzed over the time course of the trial, in steps of 0.5 s, to evaluate the time point of the feedback. Examples of the time course of the error rate (percentage of false classifications), determined by 10-by-10-fold cross validation, are presented in Fig. 8. The presented error curves were obtained during basic training (step 1; dotted line) versus letter selection (step 4; solid line). The latter is based on 5 consecutive sessions of one training day (mean accuracy: 65.8%, SD = 4.2). It can be seen that the error rate decreases slowly during the presentation of the letters; the lowest error score or, in other words, the best classification was achieved at 7.5 s. When considering the best 4 runs of this training day only, the error rate (dashed line) decreases considerably during the time interval 6.0–7.5 s. This observation indicates that the performance varies considerably within one session. Hence, moderate overall accuracy may be due to single runs

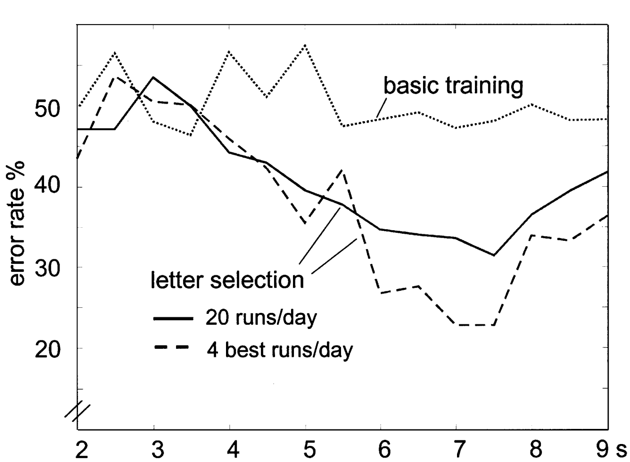

Fig. 8. Time courses of the error rate (percentage of false classifications) in 0.5 s intervals, calculated by using a 10-by-10-fold cross validation of a linear discriminant: Error rate during basic training (dotted line) and error rate during letter selection, based on the data of 5 sessions (20 runs; solid line) versus the 4 best runs (dashed line) of one training day.

of low performance, in which, for example, the patient was not able to maintain his attention to the task.

3.3. Copy spelling

To estimate the performance of 'copy spelling' (step 5), the number of correct decisions per minute was determined. Given a trial length of 8 s, a maximum of 7.5 decisions per minute could be reached in the case of 100% accuracy. During 'error ignoring' training an average of 4.6 decisions/min (SD = 0.4) was obtained over a total of 99 words of 4–8 letters each. When using the real spelling mode, where the patient had to select the 'delete' function to correct errors, the spelling rate varied largely from session to session, e.g. between 0.2 and 2.5 letters/min.

4. Discussion

The results presented here, even though obtained in a single case, revealed that it was possible for a patient suffering from a severe disease of the central nervous system, to attain self-control over specific frequency components of sensorimotor EEG rhythms. At the end of the reported training procedure, this patient was able to voluntarily produce two distinct EEG patterns, which are associated with defined mental states, motor imagery versus intended relaxing. Of special interest is that the patient is able to use this mental strategy for BCI control, such as e.g. cue-guided cursor movement or letter selection. With the achieved level of 70% accuracy in letter selection training, verbal communication was possible by means of a spelling device. This allowed the patient to write with a rate of approximately one letter per minute.

It might be argued that the patient was not able to focus his attention to the mental task for the entire training phase per day (up to 2 h), with only short breaks between sessions. Taking into account that the estimates of online classification accuracy used in this study are based on sessions of 80 trials, requiring permanent concentration to the task for a period of 15 min, it can be expected that shorter periods of communication may be completed with higher performance. In fact, regarding single runs of 20 trials an accuracy up to 90% was repeatedly obtained. The problem of high variability in performance, however, remains an unsolved issue, in particular when using an 'externally paced' BCI system (Pfurtscheller and Neuper, 2001), where specific mental states have to be generated in response to an external event within a predefined time window. Hence, an internally paced mode ('asynchronous BCI'; Birch and Mason, 2000), allowing the user to intend a mental state independently, may have essential advantages for the communication performance.

4.1. Changes of ERD/ERS patterns over training sessions reflect plastic changes of the sensorimotor cortex

An important question was whether this patient could produce similar EEG changes in sensorimotor areas by motor imagery to able-bodied subjects (Schnitzler et al., 1997, Neuper and Pfurtscheller, 1999). A number of studies suggest that motor imagery and actual movement performance share a similar neural network. Recent studies using functional magnetic resonance imaging (fMRI) verified that imagined movements can cause significant activation in the primary motor and premotor areas (e.g. Porro et al., 1996; Roth et al., 1996). Activation of the primary motor cortex (observed by fMRI) in response to imagined motor activity was not only found in healthy subjects, but also reported for a limb-amputated patient (Ersland et al., 1996) as well as for a totally paralyzed patient suffering from the 'locked-in-syndrome' (Mao et al., 1998). In the latter study, functional activation during imagination of sequential finger tapping was found mainly in the contralateral primary motor and premotor regions. A recent fMRI study in a group of tetraplegic patients suffering from trauma-related spinal cord injury has shown that chronically (up to 5 years) de-efferented sensorimotor representation areas still respond to movement attempts, displaying only minimal somatotopical reorganization (Shoham et al., 2001). Further evidence in favor of activation of neural circuitry in primary motor areas during mental motor imagery comes from transcranial activation studies. They support that the effects of motor imagery on primary motor cortical representations reflect rather cortical than spinal excitability changes (e.g. Kasai et al., 1997; Abbruzzese et al., 1999). These results document that paralyzed patients may retain the ability to generate neural signals for motor control, although their motor pathway may be severely interrupted. As revealed by ERD/ERS analysis in this study, the specific training in motor imagery tasks may produce physiologic changes in the sensorimotor cortex. This training effect may indicate sensorimotor cortex plasticity (Sanes and Donoghue, 2000).

4.2. Human–computer interaction and issue of feedback

As noted in Section 1, the goal of this study was to take advantage of both, the learning progress of the individual patient and, simultaneously, of the 'learning capability' of the classifier. The management of system–user interactions has been considered as one of the most difficult issues in development of EEG-based communication (Vaughan et al., 1996). The problems that can arise in this type of human–computer interaction have been described previously as 'Man–Machine–Learning Dilemma' (Pfurtscheller et al., 1997; Pfurtscheller and Neuper, 2001). This implies that two systems (human being and machine) have to be adapted to each other simultaneously to achieve an optimal outcome. The starting point of this adaptation is the training of the computer to recognize individual EEG patterns. During this initial phase, no feedback is provided to prevent interference of mental imagery with processing of feedback.

As soon as feedback is provided, it may have positive as well as negative effects. Correct responses are a source of positive reinforcement, which may lead to an enhancement of the target EEG pattern, whereas feedback of false responses may elicit frustration, which in turn is likely to be associated with a widespread EEG desynchronization. The effects of psychological variables, such as motivation, attention and learning history are not yet fully understood and a matter of current research (Kübler et al., 2001a). The visual feedback (cursor, letter, etc.) is likely to result in further variations of the EEG patterns. As shown in this and other studies (e.g. Flor et al., 1996), the process of learning changes EEG frequency patterns. In general, continuous feedback has been successfully used to achieve operant control over the spontaneous EEG (Wolpaw et al., 1991; Sterman, 1996, Neuper et al., 1999). There is further evidence, however, that visual feedback can either facilitate or disturb EEG control, and that these effects vary across subjects (McFarland et al., 1998). In the present case study, visual information processing of the moving feedback stimulus may have interfered with the mental task, especially in the 'relax' condition, and therefore, may have impaired EEG self-regulation. Delayed feedback at the end of the trial appeared to facilitate relaxing or band power increase when required.

4.3. Practical feasibility of tele-supported BCI training

Beside the changes of EEG patterns according to the patient's learning progress, also adaptations of the classifier can contribute to the communication performance (see, for example, Guger et al., 2001). This implies not only the implementation of various types of parameter estimation methods and classification algorithms, but also classifier updates after one or multiple sessions. This task usually requires an expert on site, who is familiar with the hardware and software components of the system. The practical problem is that severely handicapped patients most often cannot be transferred to the laboratory for training. On the other hand, it is very time consuming and costly, or even impossible for the 'BCI-expert', to visit the patient repeatedly for training purposes. In case of such practical limitations, the proposed telemonitoring system (Müller et al., 2003) offers the advantages of a video conference situation. The training is supervised on-line by the scientist and the patient and caregiver can be immediately instructed, corrected, supported and reinforced. Additionally, as revealed by comments of patient, caregiver and psychologist, direct contact via video conference had very important social aspects and contributed to the motivation of all involved in the BCI training. Another notable advantage was that the remote-control function permitted direct access to the BCI system used for the patient's training. This means that EEG data could be visually monitored online and transferred to the technical laboratory for analysis nearly without delay. This provided the possibility of frequent adaptation of feature extraction and classification, based on EEG changes during training.

Summarizing, the reported case study demonstrates that the proposed adaptive procedure, EEG feedback training of the patient and concomitant 'learning' of the system, may improve actual levels of communication ability in locked-in patients. The possibility to control the system and supervise the training from a distant geographical location facilitates clinical application of BCI training and, more generally spoken, may contribute to improve quality of life in a larger number of severely paralyzed patients.

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