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Motor imagery and action observation: Modulation of sensorimotor brain rhythms during mental control of a brain–computer interface

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ABSTRACT

Objective: This study investigates the impact of a continuously presented visual feedback in the form of a grasping hand on the modulation of sensorimotor EEG rhythms during online control of a brain–computer interface (BCI).
Methods: Two groups of participants were trained to use left or right hand motor imagery to control a specific output signal on a computer monitor: the experimental group controlled a moving hand performing an object-related grasp ('realistic feedback'), whereas the control group controlled a moving bar ('abstract feedback'). Continuous feedback was realized by using the outcome of a real-time classifier which was based on EEG signals recorded from left and right central sites.
Results: The classification results show no difference between the two feedback groups. For both groups, ERD/ERS analysis revealed a significant larger ERD during feedback presentation compared to an initial motor imagery screening session without feedback. Increased ERD during online BCI control was particularly found for the lower alpha (8–10 Hz) and for the beta bands (16–20, 20–24 Hz).
Conclusions: The present study demonstrates that visual BCI feedback clearly modulates sensorimotor EEG rhythms. When the feedback provides equivalent information on both the continuous and final outcomes of mental actions, the presentation form (abstract versus realistic) does not influence the performance in a BCI, at least in initial training sessions.
Significance: The present results are of practical interest for classifier development and BCI use in the field of motor restoration.

1. Introduction

Brain computer interfaces (BCIs) aim at providing users with an alternative output channel other than the normal output path of the brain, i.e. the efferent nervous system and muscles. The main purpose of a BCI is to detect changes in brain signals that are related to human intention, typically electrical signals resulting from neural firing, and by using an algorithm, to translate this signal in order to control an output device (for a review see Wolpaw et al., 2002). The most important clinical applications of BCI systems include brain-derived communication in paralyzed and locked-in patients (Birbaumer et al., 1999; Neuper et al., 2003) and restoration of motor function in patients with spinal cord lesions (Pfurtscheller et al.,2000, 2003; Müller-Putz et al., 2005) and chronic stroke (Birbaumer et al., 2006). For many years, event-related desynchronization and synchronization (ERD/ERS) patterns have been utilized as important features in motor related BCI systems, and the discrimination between right hand and left hand motor imagery has shown to be very useful for ERD-based classification (Pfurtscheller et al., 1997; Neuper et al., 1999, 2005, 2006; Pfurtscheller and Neuper, 2001).

To date, much BCI research has focused on the development of powerful signal processing techniques to enable high classification accuracy of the generated electroencephalogram (EEG) signals (for a recent review see e.g., Pfurtscheller et al., 2006a). However, there is a lack of systematic studies involving relevant aspects of the experimental (training) task, focusing on the person interacting with the technical system. A successful operation of BCI depends, however, to a great extent on the degree to which neural activity can be voluntarily controlled. Therefore, approaches to the training of users to control a BCI, also taking into consideration the specific target application, play an important role. For example, different training protocols and feedback techniques may be more or less efficient depending on whether the user's task is to drive a cursor on a computer screen (Wolpaw et al., 1991), to select certain

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characters or icons for communication purposes (Birbaumer et al., 1999; Kübler et al., 2001; Neuper et al., 2006; Scherer et al., 2004), or to acquire control of a neuroprosthesis to restore grasping (Müller-Putz et al., 2005; Neuper et al., 2006).

Since BCI systems use immediate, typically visual feedback of performance, the influence of the visual feedback presentation should be considered. For instance, there is some evidence that a rich visual representation of the feedback signal, e.g., in the form of a 3-dimensional video game or virtual reality environment, may enhance the learning progress in a BCI task (Pineda et al., 2003; Ron-Angevin et al., 2005; Pfurtscheller et al., 2006b). Based on these results, it seems plausible to expect that the visual display itself has an important potential to improve the control of a person over his/her brain activity. In particular, the mentioned studies suggest employing rather realistic and engaging feedback scenarios, which are closely related to the specific target application. For example, one could expect that observing a realistic moving hand should have a greater effect on the sensorimotor rhythms than watching an abstract feedback in the form of a moving bar (Pfurtscheller et al., 2007).

Another important point to consider is, however, that the processing of such a realistic feedback stimulus may interfere with the mental motor imagery task, and therefore, in some cases, impair the development of EEG control. Motor imagery, described as the mental rehearsal of a motor act without overt movements by muscular activity, is assumed to involve to a large extent the same cortical areas that are activated during actual motor preparation and execution (Jeannerod, 2001). Similar brain signals, i.e. oscillations in the mu and beta frequency bands, are reactive to both motor imagery (Pfurtscheller and Neuper, 1997, 2001; Neuper et al., 2006) and observation of biological movement (e.g., Hari et al., 1998; Cochin et al., 1998; Babiloni et al., 2002; Muthukumaraswamy et al., 2004; Oberman et al., 2007; Pfurtscheller et al., 2007). Therefore, it is not unlikely that a realistic feedback presentation, showing, for instance, a moving arm grasping an object, may interfere with the motor imagery related brain signals used by the BCI. This may play a critical role when using the BCI for neuroprosthesis control in tetraplegic patients with spinal cord injury (Pfurtscheller et al., 2000, 2003; Müller-Putz et al., 2005; Neuper et al., 2006). In that case, indeed, the feedback provided during BCI-controlled grasping is visual, i.e. the observation of the own moving hand. There is evidence from functional magnetic resonance imaging (fMRI) studies that this kind of action observation, i.e. the observation of manual actions, such as grasping a cup and raising it to the mouth, is associated with activation of premotor cortical structures (Buccino et al., 2001).

The goal of the present study was to explore how different types of visual feedback affect the EEG activity (i.e. ERD/ERS patterns) during BCI control. In this context, at least two aspects are crucial: (i) the exact manner of how the brain signal is translated into the feedback signal (i.e. the amount of information provided by the feedback) and (ii) the properties of the feedback stimuli. In the present study we compared two presentation types, abstract versus realistic feedback, while keeping the information provided by the feedback equivalent. The abstract feedback condition corresponded to the standard training protocol of the Graz-BCI (cf. Neuper et al., 1999; Pfurtscheller and Neuper, 2001), whereas in the realistic condition, online EEG parameters were used to drive a video presentation showing an object-directed grasp from the actor's perspective. This study has clear implications for both the influence of feedback type on BCI performance and the reactivity of sensorimotor rhythms during the complex interplay between motor imagery, feedback processing and movement observation (i.e. observation of hand movement during hand motor imagery).

2. Methods

2.1. Subjects

The original sample consisted of 23 healthy subjects (aged 23.04 ± 1.64 years; 14 women, 9 men) who participated in four experimental sessions on different days. All were right-handed, without any medical or psychological disorders (according to self-reports), and had normal or corrected to normal vision. All participants were initially naive to the experiment and gave informed consent after the experimental procedure had been explained to them. After completion of the whole series of experiments they received a fee for their participation. Three subjects' data were excluded from analysis due to bad quality of the EEG recordings.

2.2. Data recording

In the first (screening) session, the EEG was recorded from nine sintered Ag/AgCl electrodes placed at positions C3, Cz and C4, as well as positions 2.5 cm anterior and posterior to these (see Fig. 1A). The reference electrode was located at the left mastoid, ground electrode was located at position Fz. Electrode impedance was kept lower than 5 kOhm. The acquired signal was filtered between 0.5 and 100 Hz (2nd order, attenuation 40 dB) and sampled with 250 Hz. An additional 50 Hz notch filter was applied to avoid power line contamination. Based on the screening data, three bipolar channels covering C3, Cz and C4 were individually selected for the recordings in the further (feedback) sessions (see selection procedure described below).

In parallel to the EEG, electromyogram (EMG) data (bandpass 0.5–100 Hz; sampling rate 250 Hz) obtained from the right and left ventral forearm (*m. digitorum profundus*) was collected to control for muscle activity potentially involved in motor imagery.

2.3. Procedure

Each subject participated in a series of four experimental sessions: one screening and three feedback sessions. In the screening session, sitting in a comfortable armchair, subjects had to imagine left and right hand movements, following a fixed repetitive time scheme (see Fig. 1B). Each trial started with the presentation of

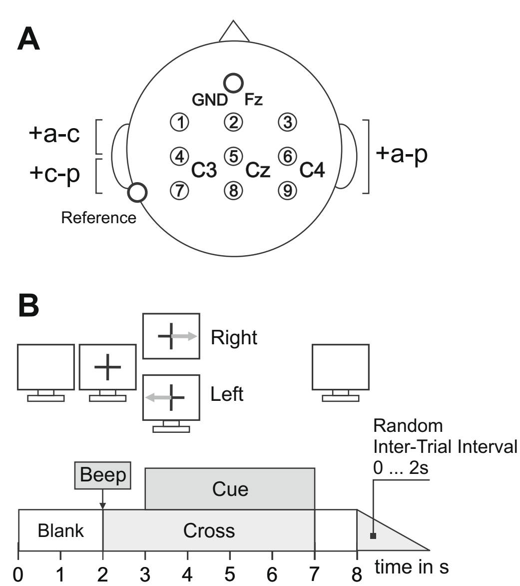

Fig. 1. Electrode setup (A) and timing of the paradigm used in screening sessions (B).

an acoustical warning tone and a fixation cross (second 2). One second later, an arrow (cue) pointing to the left (left hand) or to the right (right hand) specified the motor imagery task to perform. Subjects were instructed to imagine performing a grasping movement (i.e. the kinesthetic experience of movement) with their right or left hand, while their arms rested relaxed on the arm rest. They had to perform the motor imagery for 4 s, until the screen content was erased (second 7). After a short pause (random duration between 1 and 3 s) the next trial started. Each training run consisted of 40 trials with 20 trials per class (left/right) presented in randomized order. Five runs were recorded for each subject.

After the screening session, the participants were matched for achieved classification accuracy and randomly assigned to one of two experimental groups, receiving different types of feedback in the subsequent sessions. One group ($n = 10$) received 'abstract' feedback, which largely corresponded to the standard Graz-BCI protocol (Neuper et al., 1999; Pfurtscheller and Neuper, 2001). Following the time scheme and stimuli of the screening protocol (Fig. 2B), a continuously moving feedback bar was placed over the arrow (cue stimulus); it appeared 0.5 s later than the cue and was presented over a 4-s period. The subjects' task was, depending on the direction of the arrow, to extent the bar horizontally toward the right or left monitor edge and to keep it as long as possible in the correct half of the screen. Subjects were informed that right hand motor imagery would shift the bar to the right, and left hand motor imagery to the left. The direction as well as the length of bar extension was controlled by the online algorithm described below. In the case that the subject could successfully drive the bar to the required side of the screen for at least 3 s, reinforcement was given in form of an additional 'reward' signal: a small square, presented at the target boundary of the screen at the end of the trial (second 8), informed the subject about his/her correct performance.

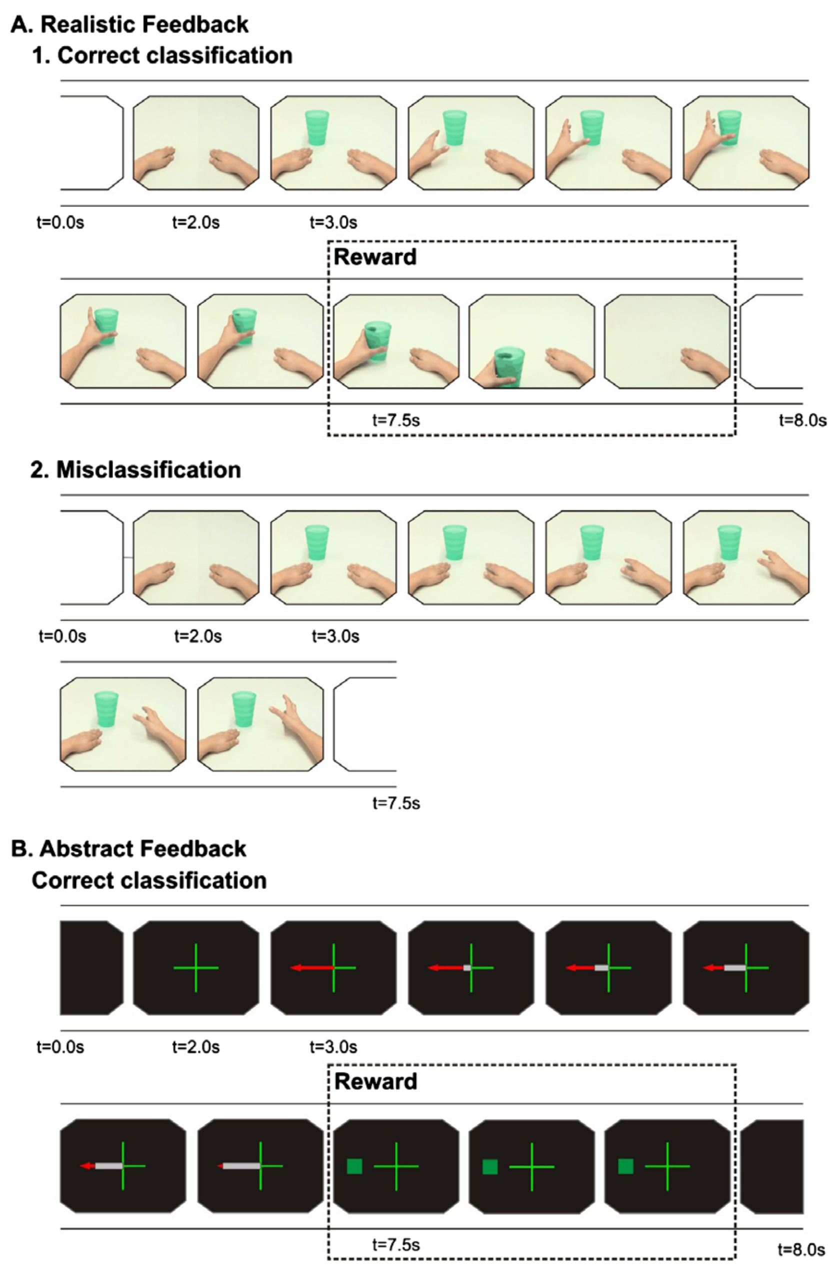

Fig. 2. Examples of feedback sequences for realistic (A) and abstract (B) feedback type in 'left hand' trials. For the realistic feedback, both a correctly classified trial (A.1) and a misclassified trial (A.2) are displayed.

The second group ($n = 10$) received 'realistic' feedback in the form of a short movie, where (according to their brain patterns caused by the required motor imagery) a right or left hand was moving to reach a target object (i.e. a glass) (see Fig. 2A). A digitized video sequence showing two real human forearms from the first person's perspective was presented on the screen. At the beginning of the trial (i.e. second 2) a frozen image of both arms resting on an empty table was shown and, after one second, a glass appeared on the screen (second 3). The initial position of the glass, which was placed either on the right or left part of the screen, served as cue indicating the required side of movement. For example, if the glass appeared on the left side, the subject had to imagine a left hand movement and, in case of correct classification, the left hand started moving to reach the glass and finally grasped it. Analogous to the bar movement in the abstract feedback, the selection of the 'responding' hand and the movement trajectory were continuously controlled by the online classifier. The rewarding grasping of the glass and raising it at the end of the trial corresponded to the 'reward' signal in the abstract condition, i.e. it was only achieved when the correct hand was selected for at least 3 s during the feedback period. In both feedback conditions (experimental groups), subjects performed three runs with 40 trials each per session.

2.4. Psychological assessment

Before the first experimental session (screening), the participants were asked to complete a German translation of the "Vividness of Mental Imagery Questionnaire" (VMIQ; Isaac et al., 1986) to assess their ability of mental imagery. Prior to each EEG session we assessed the temporary mood of the participants by means of a self-report questionnaire describing the actual mood on several dimensions (e.g., activation, anger, anxiety, calmness, weakness). As assessed by means of analysis of variance (ANOVA), no significant group and session differences were found with respect to these control variables.

2.5. Signal processing, classification and online feedback

From the screening EEG data band power features were computed by band pass filtering the EEG signal, squaring and averaging the samples in the analyzed 1-s time windows. From this averaged value the logarithm was calculated. For classification of left versus right hand trials Fisher's linear discriminant analysis (LDA) was applied to the band power estimates (sample-by-sample). To extract the relevant parameters (i.e. the most relevant frequency components and electrode locations) for each participant, the sequential floating forward selection (SFFS) feature selection algorithm (Pudil et al., 1994) was applied to the data. The SFFS method is an iterative process. In every iteration loop, at a first step, the most relevant features with respect to some objective (or fitness) function are included into the (initially empty) feature set (sequential forward selection). After this, the new feature combinations are evaluated and the least relevant features are excluded (sequential backward selection). These steps are repeated until the desired number of features is obtained. Three independent analyses were performed on three different bipolar electrode combinations (same for both hemispheres): anterior–central (a–c), central–posterior (c–p), anterior–posterior (a–p) (see Fig. 1A). These setups allow for refining both electrode spacing (small versus large distance) and location (more anterior versus posterior).

The motor imagery period of each trial was subdivided into $N = 7$ overlapping time intervals of 1-s length and a time-lag of 0.5 s. For each channel and interval 72 overlapping frequency components between 8 and 30 Hz with bandwidths of 2, 4, 6 and 8 Hz were calculated. With the features obtained from each interval individual SFFS runs were computed. The task was to identify four features which best discriminate between the two brain patterns (left versus right hand) within the 4-s motor imagery period. The selected bipolar derivation for the channels C3 and C4 were used to compute online feedback. A 10×10 cross-validation procedure was applied to avoid over fitting and enhance the generalization of classification results (Duda et al., 2001).

In the feedback sessions, the system used the individual classifier of each participant to translate the user's motor imagery into a continuous output, which was presented as online feedback on a computer screen as described above. For both feedback modalities the LDA distance, that is the distance of the current sample to classify and the decision border, was reported back to the participant. In the case of abstract feedback, the LDA distance was mapped to the bar graph length; in the case of realistic feedback, the LDA distance was linearly mapped to a frame in the movie sequence. The direction of the feedback, that is the class information, was given by the sign of the LDA distance. To enhance the class distinction for participants the LDA distance was weighted by offline-calculated gain factors, computed during classifier setup, which lead the mean deflection for each direction to the middle of each screen half for the abstract feedback or the middle of each movie sequence for the realistic feedback. After the first feedback session the SFFS method was applied to the feedback data. Each time the new classification results gained 5% of accuracy compared to the online performance, the classifier was adjusted to the new findings. This was the case in 14 out of 20 subjects.

2.6. ERD/ERS analyses

In a first step of analysis all EEG trials were visually controlled for artifacts and contaminated trials were discarded. For convenient data inspection, we computed time-frequency maps of ERD/ERS for each participant, session and task (i.e. right versus left hand). The resulting ERD/ERS maps represent plots of significant ERD (percentage band power decrease) and ERS (power increase) in narrow bands within a given frequency range (e.g., 6–40 Hz; for further details see Graimann et al., 2002). A 1-s time interval at the beginning of the trial (0.5–1.5 s) was used as reference interval (R). As activation interval (A), the time period from 3.5 to 6.5 s (imagery/feedback period) was considered (see Fig. 1B). Based on the results of the time-frequency maps, we computed the ERD/ERS in two alpha/mu (mu1: 8–10 Hz, mu2: 10–12 Hz) and two beta (beta1: 16–20 Hz, beta2: 20–24 Hz) frequency bands by employing the traditional ERD/ERS method (Pfurtscheller and Lopes da Silva, 2005).

For statistical analyses, we used the ERD/ERS values obtained from the right (recording position C4) versus left sensorimotor cortex (recording position C3), temporally aggregated over the imagery/feedback period (3.5–6.5 s). In all statistical analyses, degrees of freedom were corrected for violations of the sphericity assumption by means of the Huynh–Feldt procedure. The probability of a Type I error was maintained at 0.05.

3. Results

3.1. Classification results

3.1.1. Relevant features obtained from the screening data

The results obtained from the selection procedure of relevant input features are summarized in Fig. 3. It shows histograms of the identified frequency components averaged over all 20 subjects, separately for each hemisphere (electrode positions C3 and C4). As can be seen, for the majority of the participants frequency components in the alpha band, especially components above 10 Hz, were selected. In contrast to the clear peak in the alpha range, the fre-

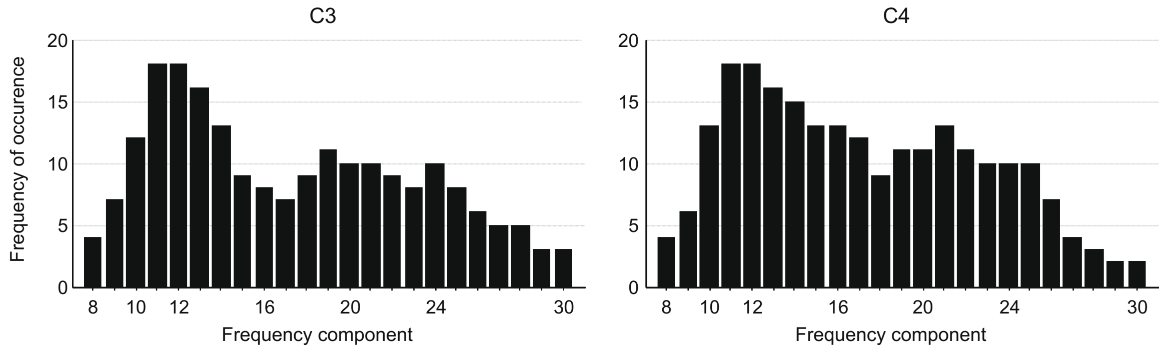

Fig. 3. Relevant frequency components for the discrimination between left and right motor imagery obtained for the electrode positions C3 and C4. The histograms show the frequency of selection of each frequency component (x-axis) over all subjects.

quency distribution of relevant beta band components across subjects was more widespread, indicating higher variability between subjects.

The mean classification accuracy (at best classification time point) obtained over all participants ($n = 20$) was approx. 77% (i.e. abstract feedback group: 77.5 ± 9.1, realistic feedback group: 77.0 ± 5.6). The majority of subjects reached values between 70% and 85% accuracy; the results of only 2 participants were below 70% and those of 3 participants higher than 85%.

3.1.2. Classification performance during feedback sessions

To compare the classification results of subjects who received realistic versus abstract feedback in the three feedback sessions, a repeated measures analysis of variance (ANOVA) was computed with type of Feedback as between- and Session as within-subjects factor. The results did not reveal any significant main effects or interactions, indicating that the performance was similar for both groups in all sessions. The mean classification results over feedback sessions were approx. 68% (session 1: 68.6 ± 11.4; session 2: 67.2 ± 10.4; session 3: 67.5 ± 11.3) for the abstract feedback group and approx. 70% (session 1: 69.6 ± 9.4; session 2: 70.8 ± 9.2; session 3: 69.9 ± 6.5) for the subjects who received realistic feedback. Note that for the online classification in the feedback sessions, a classifier built on a distinctive data set (i.e. data of the screening session without feedback) was applied. Therefore, classification results of screening and feedback sessions are not directly comparable.

3.2. ERD/ERS results

Fig. 4 compares the grand average time-frequency representation of significant ERD values (at electrode positions C3, Cz and C4) in the screening and the first feedback session. In the screening data a clearly focused (contralateral) ERD of especially alpha/mu band components can be observed during motor imagery. In both feedback groups (abstract and realistic) a strong increase of ERD during observation of the feedback stimuli is obvious. In contrast to the screening data, ERD during feedback becomes more widespread (i.e. it is present at all electrode positions) and involves to a large extent also beta band components.

In order to analyze the potential influence of the feedback modality on the ERD/ERS patterns during task performance in the different sessions, we performed a repeated measures ANOVA on the ERD/ERS data using the Feedback type (i.e. abstract versus realistic) as between-subjects variable and Electrode position (C3 versus C4), Task (left versus right hand imagery), Session (4 levels: sessions 1 to 4) and frequency Band (4 levels: mu1: 8–10 Hz, mu2: 10–12 Hz, beta1: 16–20 Hz, beta2: 20–24 Hz) as within-subjects variables. In addition, we performed two $2 \times 2 \times 4 \times 4$ ANOVAs using the variables Electrode, Task, Session and Band as

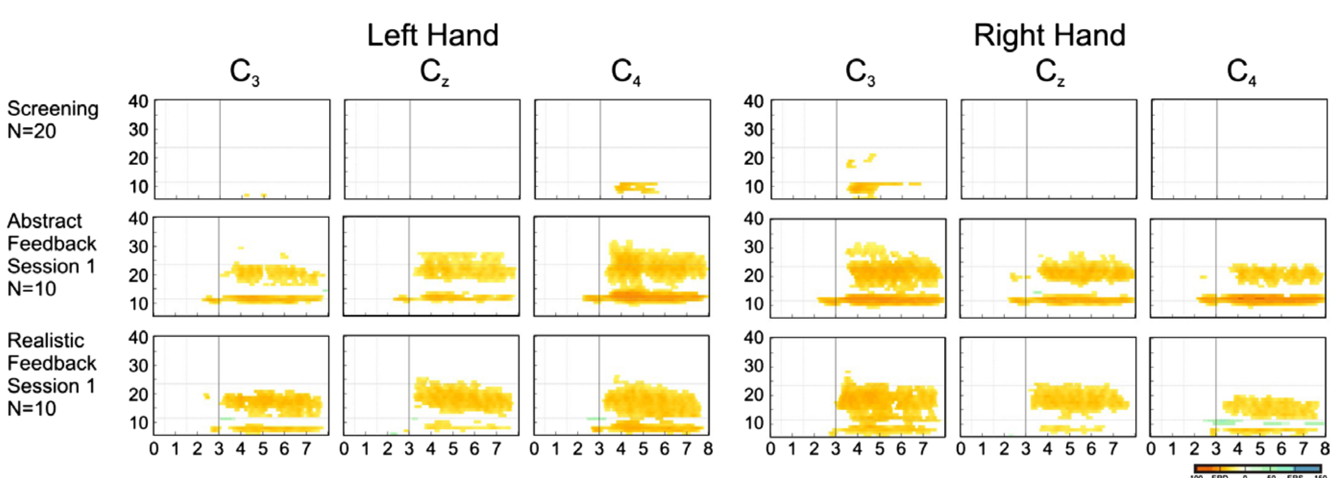

Fig. 4. Grand average time-frequency representation of significant ERD values (marked in red) at electrode positions C3, Cz and C4 for the screening and the first feedback session, separately for the two feedback groups (abstract versus realistic) and both experimental tasks (left hand versus right hand trials). The maps are plotted for the whole trial (0–8 s; x-axis) and for the frequency range of 4–40 Hz (y-axis). A vertical line indicates cue onset (second 3). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this paper.)

Table 1
Summary of significant *F*-values[a] for ERD/ERS analyses.

	ANOVA effects		
	Whole sample ($n = 20$) FB (2) × Electrode (2) × Task (2) × Session (4) × Band (4)	Abstract FB ($n = 10$) Electrode (2) × Task (2) × Session (4) × Band (4)	Concrete FB ($n = 10$) Electrode (2) × Task (2) × Session (4) × Band (4)
Electrode × FB	$F(1,18) = 10.24^{**}$		
Task × FB	$F(1,18) = 10.65^{**}$		
Electrode × Band × FB	$F(3,54) = 14.39^{**}$		
Electrode			$F(1,9) = 19.36^{**}$
Task			$F(1,9) = 21.59^{**}$
Session	$F(3,54) = 5.49^{*}$		$F(1,9) = 21.59^{**}$
Band	$F(3,54) = 4.86^{*}$		$F(3,27) = 4.14^{*}$
Electrode × Task	$F(1,18) = 28.19^{**}$		
Electrode × Session		$F(3,27) = 6.97^{**}$	$F(3,27) = 9.53^{**}$
Task × Session		$F(3,27) = 5.33^{*}$	
Electrode × Band		$F(3,27) = 10.65^{**}$	$F(3,27) = 6.38^{*}$
Electrode × Task × Band	$F(3,54) = 9.21^{**}$		
Session × Band		$F(9,81) = 3.77^{*}$	
Task × Band	$F(3,54) = 3.35^{*}$		

[a] *F*-values 5% (∗) and 1% level (∗∗). All repeated measures tests are Huynh–Feldt corrected.

within-subjects variables for the two feedback groups separately. An overview of significant ANOVA effects is provided in Table 1.

Overall, significant differences were observed as a function of Session. This main effect is primarily due to the general larger ERD during feedback sessions than during screening. The significant main effect of Band indicates that largest ERD was obtained in the lower alpha (mu1) frequency range. As expected, a highly significant interaction between recording position and side of movement imagery (Electrode × Task) was found, which substantiates the contralateral dominance of ERD. However, this analysis failed to yield a significant main effect of the group factor, but revealed significant interactions involving the factors Feedback, Electrode, Task and Band. The pattern of results suggests a generally higher ERD over the left (as compared to the right) sensorimotor region, and a higher ERD associated with right hand than with left hand imagery for the realistic but not for the abstract feedback group. With respect to the Electrode × Band × Feedback interaction, the respective means indicate that the pronounced left hemisphere preponderance in the concrete feedback group can be traced back to a particular laterality of the upper alpha (mu2) ERD/ERS pattern.

Fig. 5 presents a detailed overview of the mean ERD/ERS values for the two feedback groups, separately for the respective task (right, left hand motor imagery), frequency band, session and electrode position (C3, C4). In general, the results show a clear difference of contralateral ERD between the screening (S1) and the feedback sessions (S2–S4). Of special interest is that such an increase of ERD was observed for all frequency bands, with the exception of the upper alpha (mu2) band, which appears to be independent of the feedback presentation.

4. Discussion

The present study was particularly performed to investigate the impact of a continuously presented visual feedback in the form of a grasping hand on sensorimotor EEG rhythms during BCI control via motor imagery. A ‘motor’ BCI, controlled by modulation of sensorimotor brain rhythms and devoted to motor restoration, allows, for instance, control of grasping in high spinal cord lesioned patients (Pfurtscheller et al., 2000, 2003; Müller-Putz et al., 2005; Neuper et al., 2006). Apart from single case studies, however, little is known about the impact of such a realistic feedback, i.e. viewing grasping movements of the own hand, on BCI operation. This is a quite complex situation: the movement of the prosthetic hand depends e.g., on the suppression of sensorimotor brain rhythms but, on the other hand, seeing the moving hand can cause a similar suppression. In the present paper we, therefore, set out to explore in a controlled study in healthy volunteers the reactivity of sensorimotor rhythms during the complex interplay between (i) motor imagery, (ii) concomitant processing of feedback, and (iii) the special impact of ‘realistic’ feedback involving action observation (i.e. observation of hand movement during hand motor imagery). In the following discussion of our results we address these aspects separately.

4.1. Screening results: ERD/ERS during unilateral hand motor imagery

Rolandic mu and beta rhythms in humans are characteristically recorded over sensorimotor areas with spectral peaks around 10 and 20 Hz (for a review see Hari et al., 1998). Both frequencies show typical reactivity in association with voluntary movements (Pfurtscheller et al., 2006b) and motor imagery (Pfurtscheller and Neuper, 1997, 2001). Also in the present study, we found a clear and locally restricted desynchronization of the mu rhythm during imagery of unilateral hand movement. Corresponding to previous results, frequency components around 10 Hz (11–13 Hz) and 20 Hz (15–25 Hz) showed highest significance for the classification of the imagery-related EEG segments (Neuper and Pfurtscheller, 2001; Neuper et al., 2005; Pfurtscheller et al., 2006c).

The mean classification accuracy of approx. 77% obtained over the whole sample ($n = 20$) as well as the proportion of good versus bad performers is in line with previous results obtained with the standard Graz-BCI protocol (see e.g., Pfurtscheller and Neuper, 2001). Comparing these classification results with the literature, one should take into account that, in contrast to many other studies, this one has been performed using (i) naive subjects, without any preselection or inclusion restriction and (ii) two channels only were used to compute online feedback.

4.2. ERD/ERS and performance in feedback sessions

As expected from previous studies (e.g., Neuper et al., 1999; Shenoy et al., 2006), our data show that the ERD/ERS patterns used for BCI control can change substantially from the offline screening session to online control. In contrast to the simple motor imagery task during screening, motor imagery and simultaneous processing of feedback clearly increased ERD over sensorimotor areas. Regarding specific frequency bands, our data show that largest ERD was

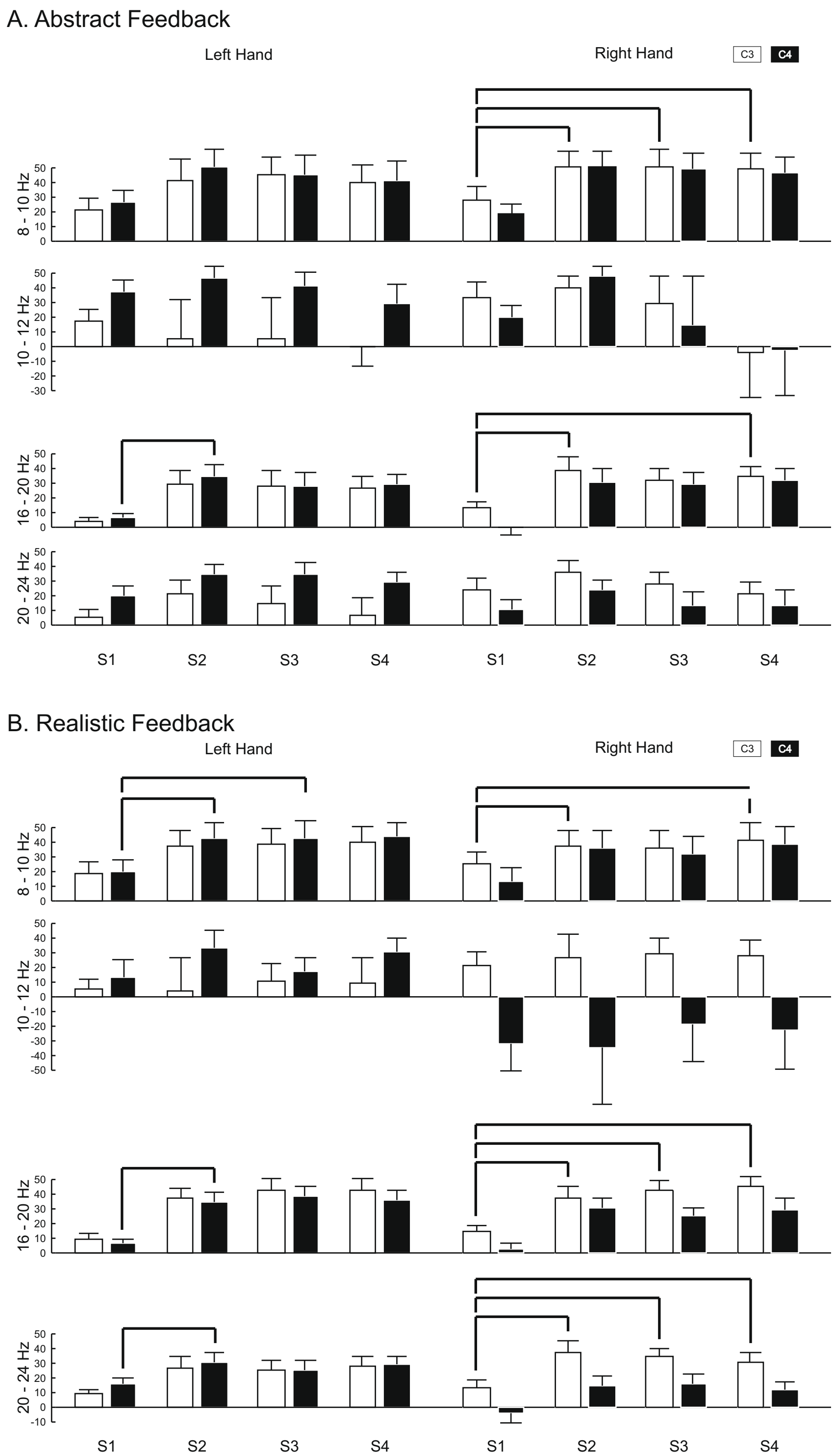

Fig. 5. Mean ERD/ERS values (i.e. mean and standard error) obtained for left hand (left panel) versus right hand imagery (right panel) for the 4 analyzed frequency bands (i.e. 8–10, 10–12, 16–20, 20–24 Hz), the four experimental sessions (S1–S4) and left (C3, white bar) versus right (C4, black bar) sensorimotor derivation. Data are shown separately for the subjects who received abstract (A) and realistic feedback (B). Significant differences between sessions (restricted to contralateral ERD) are indicated.

generally obtained in the lower mu (8–10 Hz) frequency range, which increased significantly from screening to feedback sessions. Such an increased ERD during feedback was also found for the beta bands (16–20, 20–24 Hz), but more prevalent in the group that received realistic feedback.

The most striking result is, however, that only ERD in the upper mu (10–12 Hz) band, which shows most pronounced hemispheric asymmetry and contributes for the most part to the differentiation of left hand and right hand imagery trials, does not differ between screening and feedback sessions. That is, the signal which is used as the main input feature for the BCI, seems to be independent of and is not influenced by the feedback, irrespectively of its type (i.e. abstract or realistic). This result is of interest in the context of a recent BCI study addressing the issue of neurophysiologic changes related to offline and online sessions (Shenoy et al., 2006). The authors found a huge and systematic difference between brain activity during offline and online sessions, but the significant difference between tasks stayed relatively stable when going from offline to online operation. Our data now suggest that distinct aspects of the processes involved in the specific BCI control task may be reflected in reactivity patterns of different frequency bands. For example, the lower frequency mu rhythm (8–10 Hz) displays a bilateral, movement-type non-specific ERD, which increases with enhanced involvement during online BCI control. The upper frequency component (10–12 Hz), in contrast, shows a more focused and motor imagery specific pattern, which remains stable across sessions with and without feedback. In some of the subjects (i.e. participants of the realistic feedback group) imagination of hand movements led to ERD at the contralateral, but to 10-Hz ERS at the ipsilateral site, as reported earlier (Neuper et al., 1999; Neuper and Pfurtscheller, 2001).

A rather unexpected result was that there was no improvement of classification accuracy over feedback sessions. From previous research there is no doubt that performance feedback is a necessary and useful method improving learning, attention and motivation in BCI applications (Kübler et al., 2001; Wolpaw et al., 2002; Birbaumer et al., 2006). The lack of learning progress in the present study may be partly explained by the short training period including three feedback sessions only, which in some cases were quite long (i.e. up to several weeks) apart. A larger number of feedback sessions, performed in short and regular intervals, would be important to further study training progress in inexperienced BCI users. The lack of a significant learning progress may also be explained by the fact that the participants already started at a relatively high performance level.

Learning to control brain activity for driving a BCI is a complex task and in this situation, not only physiological but also psychological factors like motivation, attention or excitement may play an important role (Curran and Stokes, 2003; Nijboer et al., 2008). Such psychological factors could be influenced by the choice of feedback presentation, which might, in turn, determine the success in following BCI applications. The results of this study, however, indicate that the type of feedback (abstract versus realistic) per se does not necessarily influence the performance in BCI applications, at least in early training. These findings are contrary to the assumptions previously made from our group (Pfurtscheller et al., 2006b, 2007) and others (Pineda et al., 2003), suggesting that more stimulus-rich and realistic feedback conditions would lead to better performance and shorter training times. On the other hand, the present study compared, to our knowledge, for the first time, two experimental groups, which were carefully matched with respect to their classification results in the screening (since the initial performance level is a very important predictor for later BCI performance; see Neumann and Birbaumer, 2003) and controlled for other psychological variables like motor imagery ability and self-reports of actual mood. More importantly, the two experimental feedback conditions were exactly equivalent in terms of information content and timing.

4.3. Realistic feedback: impact of action observation

Modulation of sensorimotor brain rhythms in the mu and beta frequency band has been recently linked to the activity of the human mirror neuron system, referring to an action observation/ execution matching system, which is capable of performing an internal simulation of the observed action (for a review see Pineda, 2005; Hari, 2006). On indirect evidence of functional imaging and electrophysiological studies, a functional correspondence between action observation, internal simulation or motor imagery and execution of the motor action has been proposed (Grezes and Decety, 2001). The mu rhythm has been considered to reflect the downstream modulation of primary sensorimotor neurons by visuomotor mirror neurons in the premotor cortex (Pineda, 2005; Kilner and Frith, 2007). The underlying idea is that activation of mirror neurons by executed, imagined or observed motor actions produces asynchronous firing and, therefore, is associated with a concomitant suppression or desynchronization of the mu rhythm (Lopes da Silva, 2006).

There is evidence that the mu rhythm and beta oscillations recorded from scalp locations C3 and C4 are reduced by observation of experimental hand grasp (Gastaut and Bert, 1954; Cochin et al., 1998). Moreover, the presence of an object, indicating a goal-directed action, increases the mu rhythm suppression as compared to meaningless actions (Muthukumaraswamy et al., 2004). A previous study in our laboratory (Pfurtscheller et al., 2007) which also used an event-related experimental design like the present one, confirmed that the processing of moving visual stimuli depends on the type of moving object: viewing a moving virtual hand resulted in a stronger desynchronization of the central beta rhythm than viewing a moving cube.

In the present study, comparing the observed ERD/ERS patterns related to realistic versus abstract feedback, the impact of viewing the moving hands (as compared to the moving bar) is less clear. Although stronger motor cortex activation could be expected for the realistic feedback, our data show that realistic and abstract feedback suppressed the sensorimotor rhythms to relatively the same extent. This may be resolved by considering the 'goal-oriented' experimental task used in the present study. In both conditions, the participant's task was to drive the feedback signal (bar extension/hand trajectory) to the respective target (side of screen/position of glass) by using mental motor imagery. Interestingly, although motor activation seems to be strongest for the observation of human biological motion, there is recent evidence from neuroimaging data that premotor areas involved in the processing of biological motion are also activated by sequences of abstract stimuli, as long as they provide sequentially structured information (Schubotz and von Cramon, 2004). Areas like the inferior parietal cortex seem to be strongly linked to biological motion, whereas frontal regions like Broca's area seem to be concerned with more abstract aspects like the action goal (Koski et al., 2002). Therefore, it can be speculated that goal-orientation may also have an influence on ERD/ERS patterns during observation of a moving feedback signal. In consideration that the varying bar extension in the abstract feedback condition may be seen as a representation of the outcome of the mental action simulation, the equally strong ERD of sensorimotor activity during abstract and realistic feedback fits into this line of evidence.

In the realistic feedback, the participants watched the moving hand trying to grasp a glass, while they focused their attention on imagining performing the respective hand movement themselves. This condition may not necessarily facilitate the required motor imagery. In the case of misclassification, where the participant is required to e.g., imagine a right hand movement, but views unsuccessful grasping attempts of the animated left hand, this task may even cause some sort of interference. Such interference between observation and self-performed movements has been reported in a number of reaction time experiments, which showed that movement execution is faster when accompanied by observation of a congruent movement than when it is accompanied by observation of an incongruent movement (for a review, see Brass and Heyes, 2005).

The skill of BCI control requires for acquisition and maintenance feedback of performance and adaptation of brain activity based on that feedback (Wolpaw et al., 2002). Our results show that, when the feedback provides comparable information on the continuous and final outcomes of mental actions, the type of feedback (abstract versus realistic) does not influence the performance, at least in initial training sessions. In both conditions, the feedback stimuli seem to become closely associated with the action goal during on-line control, and therefore, are able to enhance the desired electrophysiological signals for individuals to perform accurately.

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