Research Report

Imagery of motor actions: Differential effects of kinesthetic and visual–motor mode of imagery in single-trial EEG

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Abstract

Single-trial motor imagery classification is an integral part of a number of brain–computer interface (BCI) systems. The possible significance of the kind of imagery, involving rather kinesthetic or visual representations of actions, was addressed using the following experimental conditions: kinesthetic motor imagery (MIK), visual–motor imagery (MIV), motor execution (ME) and observation of movement (OOM). Based on multi-channel EEG recordings in 14 right-handed participants, we applied a learning classifier, the distinction sensitive learning vector quantization (DSLVQ) to identify relevant features (i.e., frequency bands, electrode sites) for recognition of the respective mental states. For ME and OOM, the overall classification accuracies were about 80%. The rates obtained for MIK (67%) were better than the results of MIV (56%). Moreover, the focus of activity during kinesthetic imagery was found close to the sensorimotor hand area, whereas visual–motor imagery did not reveal a clear spatial pattern. Consequently, to improve motor-imagery-based BCI control, user training should emphasize kinesthetic experiences instead of visual representations of actions.

1. Introduction

The use of mental imagery of motor behavior plays an important role in motor skill learning [11] and rehabilitation [39]. Aside from these classical applications, motor imagery, defined as mental simulation of a movement [5,13], has been shown to represent an efficient mental strategy to operate a direct brain–computer interface (BCI) [22]. For the latter application, e.g. the control of an

external device based on brain signals (i.e., EEG signals), it is essential that imagery-related brain activity can be detected in real time from the ongoing EEG. The main goal of this research work is to establish an EEG-based communication system that should provide an alternative communication or control channel for patients with severe motor impairment [40].

It has been shown that mental imagery of motor actions can produce replicable EEG patterns over primary sensory and motor areas [2,21]. As an example, imagery of hand movements results in desynchronization of mu (8–12 Hz) and central beta rhythms (13–28 Hz), very similar to planning and execution of real movements [17]. It is even possible to distinguish between imagined right and left

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hand movements based on single-trial EEG signals [19,22,24]. These data strongly indicate a type of readiness or presetting of neural networks in sensorimotor areas during mental simulation of movement. Further evidence in favor of matching cortical activity in the contralateral hand area during execution and imagination of hand movement comes from DC potential measurements [2] and dipole source analysis of electric and magnetic fields [14].

Even though it has been well documented that imagination of simple movements elicits predictable changes in the sensorimotor mu and beta bands, which are very stable over time (i.e., small intra-subject variability), there are also conflicting results of a portion of participants, who do not show the expected imagery-related EEG changes [22]. Moreover, a diversity of time–frequency patterns (i.e., high inter-subject variability), especially with respect to the reactive frequency components, was found when studying the dynamics of oscillatory activity during movement imagination [17,25,38].

The observed individual differences in imagery-related EEG changes may be explained by varieties of motor imagery, as described by Annett [1]. In case that there is no specific instruction, the subject may, for example, either imagine self-performed action with 'interior view' or, alternatively, imagine seeing himself or another person performing actions with an exterior view (i.e., 'mental video') [4]. Whereas the first type of imagery is supposed to involve kinesthetic experiences [34], the second case may be primarily visual in character. Based on the general idea that imagining is functionally equivalent to and may share some of the brain processes associated with real perception and action [1,35], the different ways how subjects perform motor imagery are very likely associated with dissimilar electrophysiological activation patterns (i.e., in terms of time, frequency and spatial domains).

In the present study, we investigated the EEG patterns sensitive to different types of motor imagery. In particular, the instruction how to imagine action was varied to create (i) kinesthetic motor imagery (first-person process) and (ii) visual–motor imagery (third-person process). For control purposes, also 'real conditions' were examined, i.e., the execution and visual observation of physical hand movements, respectively. The goal of this study was to identify relevant features of the ongoing multi-channel EEG (i.e., electrode locations and reactive frequency components) that represent the specific mental processes. In order to determine the relevant features for recognizing the respective mental states, a neural network classifier, the distinction sensitive learning vector quantization (DSLVQ) [29] algorithm, was used. This method uses a weighted distance function and adjusts the influence of different input features (e.g. frequency components) through supervised learning.

2. Methods

2.1. Subjects

Fourteen healthy volunteers, aged 18–53 years (mean = 26.2, SD = 8.3), participated in the study. All were right-handed, without any medical or psychological diseases and/or medication and had normal or corrected to normal vision. The participants gave informed consent after the experimental procedure had been explained to them and received a small fee for their participation.

2.2. Experimental tasks and procedure

During the experiment, the participants were sitting in a comfortable armchair in front of a 17″ monitor at a distance of about 1.3 m, in an electrically shielded recording room. Four experimental tasks were performed during EEG recording. Before each task condition, verbal instructions were given, and a number of training trials were presented to the participants until they felt confident enough that they could perform the respective task.

ME	Motor execution: subjects held a small ball in their right fist, while their forearm rested on the arm rest. They were instructed to perform continuous hand movements by clenching softly the ball during indicated time periods as described below.
MIK	Imagery of hand movement ('kinesthetic'): subjects were instructed to imagine clenching softly a ball with their right hand, while their arm rested relaxed on the arm rest. They were asked to imagine the kinesthetic experience of movement while avoiding muscle tension.
OOM	Observation of hand movement: subjects observed grasping movements of an animated (right) hand. They were instructed to sit relaxed and watch the presentation on the monitor in front of them.
MIV	Imagery of hand movement ('visual–motor'): subjects were instructed to visualize right hand movements; specifically, they were asked to create a 'mental video' of the movements of the 'alien' hand they watched in the previous condition.

Besides the specific task instructions, the participants were asked to sit relaxed with eyes open and to avoid any eye movements and body movements other than requested. The correct task execution was monitored using a video system installed in the recording compartment. Subjective ratings of the vividness of the imagined movements were obtained by verbal report after completion of the respective task.

For the visual stimulus presentation (in condition OOM), a digitized video sequence of a realistic (animated) hand was presented on the screen. The animated hand was a right (open) hand which appeared at the beginning of the trial (i.e., at second 2) and remained static for 1 s. Then, it began to close (make a fist) and to open again. This action was

presented two times in a sequence lasting 3 s; thereafter, the hand remained in a static (open) position on the screen for one more second (second 7).

The experiment was divided into two blocks. One started with the visual presentation of the animated hand (OOM), the other started with the actual execution of hand movements (ME). In order to facilitate the respective imagery task, a sequence of the conditions was chosen that both imagery tasks were preceded by the corresponding 'real' task, that is, MIK followed ME, and MIV was performed straight after OOM, respectively. The sequence of the 2 blocks was counterbalanced between subjects.

Each of the 4 tasks was presented in a separate run which contained 40 trials of 8 s. Each started with the presentation of a fixation cross at the center of the monitor (second 0). A beep tone at second 2 indicated the beginning of the respective task: subjects should either watch the movements of the animated hand, or perform movements themselves, or imagine hand movements until a double beep tone marked the end of the task (second 7). During the last second of the trial (second 8), there was a blank screen. The inter-trial period until the beginning of the next trial varied randomly between 0.5 and 2.5 s. Between the different tasks, there were breaks of 3 to 5 min.

2.3. EEG recordings and preprocessing

Continuous EEG signals were recorded from 33 scalp sites (Ag–AgCl electrodes, extended 10–20 system) using an electrode cap (Easycap, Germany) fitted to the subject's head. A ground electrode was placed on the forehead. A reference electrode was placed on the left mastoid, but all EEG data were converted to common average reference prior to analysis. EOG was recorded bipolarly between 2 electrodes diagonally placed above and below the inner respectively the outer canthus of the right eye. Recording and digitization were carried out using Neuroscan Synamps amplifier with signal bandpass 0.3–50 Hz and an additional 50 Hz notch filter. The data, including trigger signals, were sampled at 250 Hz. After triggering the data, trials of 8-s length were obtained including 2 s before the beep tone. All trials were visually controlled for artifacts, and affected trials were excluded from further analyses. For data preprocessing, the software package BIOSIG [33] was used.

2.4. Signal processing

In a first step of analysis, the EEG data were subjected to an ERD/ERS time–frequency analysis [10] for purpose of convenient data inspection. The resulting ERD/ERS maps represent plots of significant ERD (percentage band power decrease) and ERS (power increase) in 2-Hz frequency bands within a given frequency range (e.g. 6–36 Hz).

To overcome the problem of high interindividual variability in ERD/ERS patterns and also according to the main purpose of this study, the results reported below concern data from further analyses, in which we applied a neural network classifier to identify the most relevant cortical regions and reactive EEG frequency components for the different experimental tasks. To this end, we addressed the questions (i) which of the 33 EEG derivations were the most relevant for the recognition of the respective experimental task and (ii) which of the frequency components of interest (in the most important derivation) were the most relevant signal features associated with a given task.

For this selection procedure, the 'distinction sensitive learning vector quantization' (DSLVQ), an extended version of Kohonen's Learning Vector Quantization algorithm (LVQ), was used (for details, see [28]). LVQ uses a reduced number of codebook vectors (labeled reference vectors) to approximate the optimal Bayesian decision borders between different classes. Each sample is classified to the label of its closest codebook vector according to a distance function (e.g. Euclidean distance); the influence of the features on the distance function is equal. DSLVQ introduces a weighted distance function which rates the influence of the features for classification: most informative features are upgraded; features that contribute to misclassification are discarded. The LVQ codebook splits the classification problem into sub-problems. By finding an optimal linear approximation for the sub-problems, the relevance of the features, which determines the correct classification, is analyzed [28]. The major advantage of DSLVQ is that it does not require expertise nor any a priori knowledge or assumption about the distribution of the data. Furthermore, not only relevant features, but also feature combinations, are identified.

For the single-trial DSLVQ analysis from each trial, two time segments of 1-s length were extracted, one was taken from the reference period (i.e., 0.5–1.5 s) the other from the task period (i.e., 3.5–4.5 s). For each segment, 14 non-overlapping frequency components between 6 and 36 Hz with a bandwidth of 2 Hz were calculated. The frequency components were computed by digitally bandpass filtering the EEG signal, squaring and averaging the samples in the analyzed 1-s time window. From this averaged value, the logarithm was calculated. The number of features was limited to 14 because of the limited number of trials. With the features computed from the reference interval (labeled as class 1) and the features extracted from the task interval (class 2) for all trials (separately for each task and for each electrode position), a DSLVQ classification was performed.

In order to obtain reliable values of the classification performance and the feature relevance, the DSLVQ method was repeated 100 times. For each run of the DSLVQ classification, a randomly selected 50% of the computed features were used for the training, and the

remaining 50% were kept to test the classifier. Each class, represented by 3 codebook vectors, was initialized with k-means clustering. The initial clustering was repeated when a codebook represented less than 5% or more than 75% of the total number of samples for a maximum of 100 retries. Finally, the classifier was fine-tuned with DSLVQ type C training (10.000 iterations). The learning rate decreased from an initial value of $\alpha = 0.05$ to $\alpha = 0$. The DSLVQ relevance values were updated with the learning rate $\alpha'(t) = 0.1 * \alpha(t)$.

3. Results

Visual inspection of the individual ERD/ERS time–frequency maps revealed event-related EEG changes in alpha and beta frequency bands, which differed dependent on the experimental task; the patterns of desynchronization and synchronization, however, varied considerably across individuals. Fig. 1a illustrates such examples of various ERD/ERS phenomena of 3 selected subjects. All of them show clear differences between kinesthetic (MIK) and visual–motor imagery (MIV): the first example (subject p16) shows clear desynchronization of lower alpha and beta band components during both kinds of imagery, even somewhat stronger with MIV than with MIK; a crucial difference is that, only with MIK, this desynchronization pattern over sensorimotor areas is followed by a beta band synchronization (beta ERS). In subject ×4, we found a clearly stronger ERD of sensorimotor alpha and beta band components for MIK than for MIV. Also in the third case (subject ×8), MIK is associated with a clear contralateral ERD of alpha and beta band components, whereas MIV is rather associated with patterns of synchronized activity (i.e., amplitude enhancement, ERS). Due to the high interindividual variability of ERD/ERS patterns, by averaging over the whole group of subjects, the observed phenomena (i.e., ERD and ERS) would cancel each other out, and the average data would not reveal clear ERD/ERS differences between the tasks.

Fig. 1b gives an overview of the topographical distribution of the classification accuracy rates for the recognition of the different tasks by means of DSLVQ analysis. The maps show a linear interpolation of the classification accuracies over all subjects, which have been plotted at the corresponding electrode positions. Red areas indicate most relevant electrode positions for the recognition of the respective task, whereas recording locations coded in blue did not provide essential information. The results show that electrodes overlying approximately the sensorimotor hand area (i.e., close to position C3) provide the best input features for the recognition of both the motor execution (ME) and the kinesthetic motor imagery (MIK) task. For the observation of hand movement (OOM), highest classification accuracies were achieved for electrodes overlying the occipital cortical areas (channels O1 and O2). This is not

surprising because visual input always affects the brain activity in occipital areas. Less clear is the topographical picture obtained for the visual–motor type of imagery (MIV), indicating some relevance of frontal and right parieto-occipital areas.

Table 1 presents the results of the single-trial analysis by DSLVQ of all subjects for two selected electrode positions, i.e., the most important sites that are very close to the sensorimotor (C3) and visual areas (O2) of the cortex. Each value corresponds to the mean classification result of the 100 DSLVQ repetitions. These data show that the highest classification accuracies, in average, were achieved for motor execution (ME) and observation of movement (OOM), both at the corresponding representation areas (i.e., at positions C3 and O2, respectively). Thus, as could be expected, the 'real' conditions yield better classification accuracies compared to the imagery conditions. However, individuals are sensitive to the task conditions in different degrees. Albeit the great variability of the classification accuracy between the participants, the classification accuracies obtained for the kinesthetic type of imagery (MIK) are in average better than the results of the visual–motor imagery (MIV).

This observation was confirmed by statistical comparisons of the obtained classification results. The classification accuracies from central (C3, C4) and occipital (O1, O2) sites were subjected to a repeated measures ANOVA with the factors TASK (4 levels: ME, MIK, OOM, MIV), REGION (2 levels: central vs. occipital) and HEMISPHERE (2 levels: left vs. right) as within subject variables. The results yielded significant main effects of TASK ($F(3,39) = 15.46$; $P < 0.001$) and HEMISPHERE ($F(1,13) = 7.9$; $P \leq 0.01$) as well as significant interactions between all involved variables. There were significant 2-way interactions between TASK × REGION ($F(3,39) = 30.6$; $P < 0.001$) and TASK × HEMISPHERE ($F(3,39) = 3.5$; $P < 0.05$) and a significant 3-way interaction TASK × REGION × HEMISPHERE ($F(3,39) = 5.52$; $P < 0.01$). Aside from the prominent TASK × REGION effect for the 'real' motor versus visual task conditions, indicating higher recognition rate for ME in central and for OOM in occipital sites, we found also significant differences between the 2 imagery tasks: whereas the recognition rate of visual–motor imagery (MIV) at any recording site was hardly above random, the classification rate for kinesthetic motor imagery (MIK) was clearly highest in the left central derivation compared to right central and occipital sites. Post-hoc comparisons of the respective means (using paired t tests) support that the recognition rate at the left central electrode site (electrode C3) was higher with kinesthetic than with visual–motor imagery (i.e., $67 > 56$; $P = 0.01$).

Furthermore, we computed the overall relevance of the frequency components estimated by DSLVQ (i.e., discriminative features of the task period with respect to those of

baseline period). The overall feature relevance was computed by ranking the frequency components of each of the 100 DSLVQ repetitions for each subject indepen-

dently and averaging the results of the DSLVQ feature relevance estimates over all subjects afterwards. The resulting values correspond to the percentage of DSLVQ
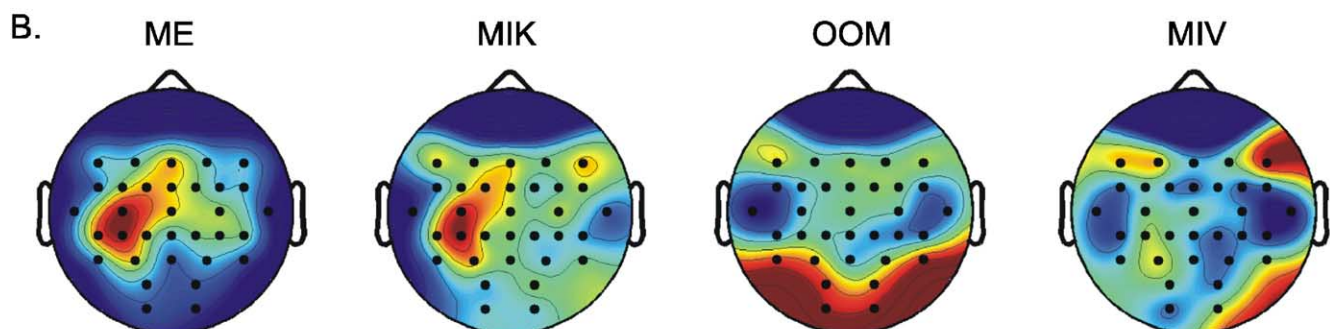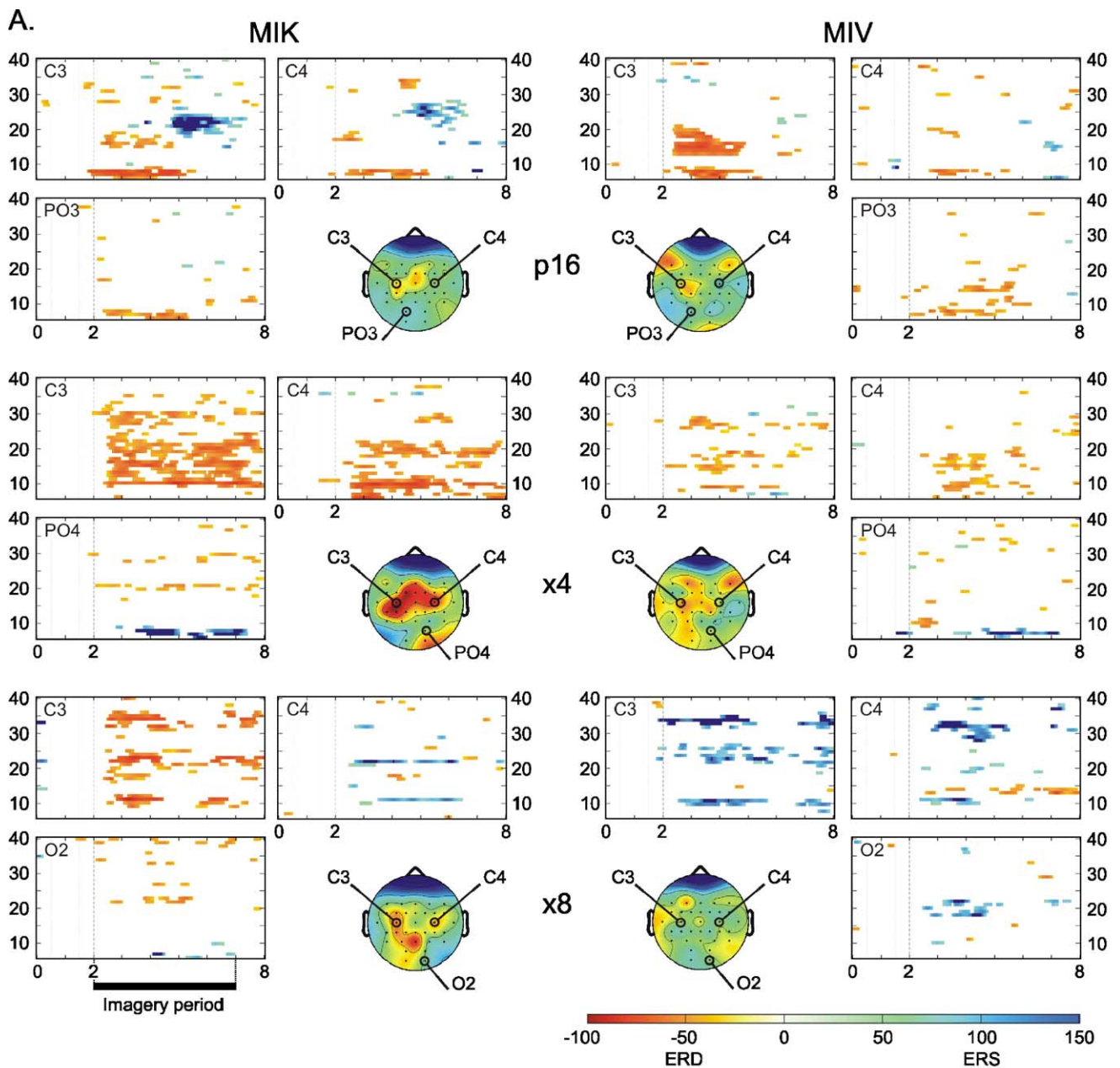
Table 1
Classification accuracy rates (%) of 14 subjects for different conditions (ME, MIK, OOM, MIV) and selected electrode positions (central position: C3 or C3′; occipital position: O2)

Subject	ME		MIK		OOM		MIV	
	Central	Occipital	Central	Occipital	Central	Occipital	Central	Occipital
l1	99	56	74	55	53	70	60	54
p16	71	44	62	52	80	82	63	59
q5	75	53	73	58	74	63	45	60
t5	91	61	52	63	60	86	52	57
t7	83	61	52	53	52	86	65	79
u5	93	57	59	54	63	83	67	52
v3	70	68	62	52	73	77	43	55
v4	58	45	69	49	64	65	63	56
v7	91	59	64	46	67	86	43	55
x1	61	59	79	58	66	74	50	49
x4	97	50	83	67	46	71	67	58
x6	67	51	55	61	64	79	55	55
x8	73	49	71	54	64	74	58	55
p19	89	64	83	50	55	79	57	63
Mean	80	56	67	55	63	77	56	58
SD	13.6	7.1	10.7	5.7	9.3	7.6	8.5	7

analyses in which the specific feature contributes to a correct classification.

Fig. 2 shows the obtained relevance values of different frequency components for the four tasks in detail. The feature relevance values for ME and MIK are compared at the central cortical area (electrode position C3), the values for OOM and MIV are shown for the occipital area (O2). Each plot shows the means of the estimated relevance values for the frequency components between 8 and 36 Hz. It can be clearly seen that the lower beta (~16–22 Hz) frequency range is the most reactive during ME. A somewhat different profile was found for MIK, where especially upper alpha or mu components (~10–14 Hz) contribute to the discrimination between rest and motor imagery. A clear picture of feature relevance was found for OOM: upper alpha components at occipital areas contribute mostly to the recognition of visual processing. Also in the case of MIV, albeit the poor classification results, alpha band components appear to be more relevant than other frequencies.

4. Discussion

Previous studies suggest that, in motor behavior representation, there is probably some overlap in the utilization of visual imagery and motor imagery [1,35,36]. For motor imagery tasks in BCI research, the subjects are usually instructed to imagine themselves performing a specific motor action without overt motor output. However, dependent on the exact manner of how subjects perform this task, the relative contribution of various aspects involved in motor imagery, such as movement intention, motor planning, or visual and kinesthetic representations may vary and, as a result, distinct processes may be involved. Our study shows that motor imagery strategies emphasizing either kinesthetic or visual–motor representations are associated with distinct EEG (ERD/ERS) patterns, with respect to spatial distribution and involved frequency components.

Several studies have demonstrated that execution and imagination of movement lead to short-lasting patterns of simultaneously attenuated (ERD) and enhanced EEG components (ERS) [17,22]. This type of pattern was called 'focal ERD/surround ERS' [37] and may characterize a focal activation of cortical areas together with a deactivation (inhibition) of neighboring or surrounding areas. This 'focal ERD/surround ERS' typically involves upper alpha (mu) (10–13 Hz) and beta (13–28 Hz) rhythms, but the specifically involved frequency components and their reactivity pattern (ERD/ERS) can differ considerably between individuals. Therefore, to characterize (and recognize) mental representation of movement in ongoing EEG

Fig. 1. (A) Examples of ERD/ERS time–frequency maps for kinesthetic (MIK) and visual–motor imagery (MIV). Data of 3 subjects (p16, ×4, ×8) illustrate diverse ERD/ERS patterns obtained at left and right sensorimotor sites (C3, C4) and at one selected derivation over parieto-occipital areas. Red color indicates significant ($P < 0.01$) power decrease (ERD), and blue color significant ($P > 0.01$) power increase (ERS). In addition, topographical maps of classification accuracy for the corresponding data are displayed in the right or left lower corner. (B) Topographical display (map) of grand average classification accuracies ($N = 14$) plotted at the corresponding electrode positions (linear interpolation), separately for the 4 experimental conditions (ME, OOM, MIK, MIV). Red areas indicate the most relevant electrode positions for the recognition of the respective task. Scaling was adjusted to minimum and maximum values obtained for each condition (ME (min/max%): 53/76, OOM (min/max%): 56/77, MIK (min/max%): 51/64, MIV (min/max%): 51/61).
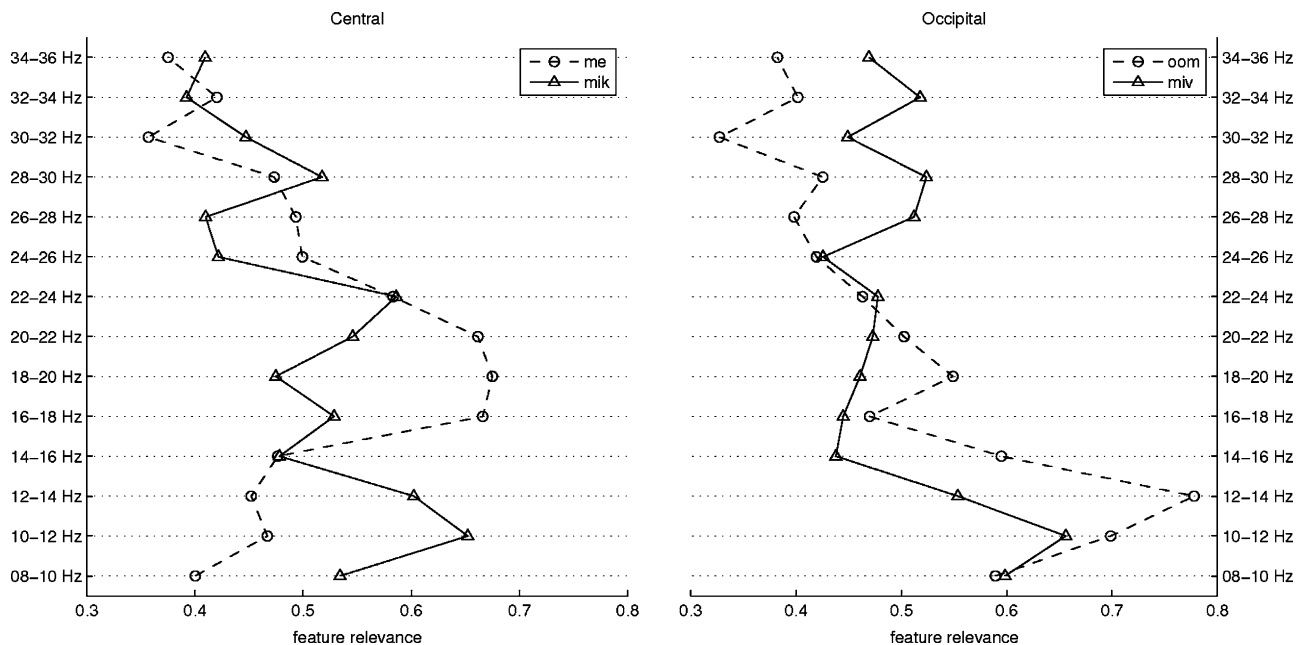
Fig. 2. Relevant frequency components found by DSLVQ. Left side: feature relevance values for ME (dotted line) versus MIK (full line) obtained at central electrode site (C3). Right side: feature relevance values for OOM (dotted line) versus MIV (full line) obtained at occipital electrode site (O2). The feature relevance value is computed by ranking the frequency components of each of the 100 DSLVQ repetitions for each subject independently and by subsequently calculating the average.

signals, it seems reasonable to adopt an individual-oriented approach, such as the use of a learning classifier (such as DSLVQ in this study).

The results obtained for the 'real' conditions, i.e., movement execution (ME) and observation (OOM), clearly show that DSLVQ classification method allows for the visualization of cortical areas involved in motor and visual processing, respectively. As expected, electrodes approximately overlying the cortical sensorimotor hand area (electrodes close to C3) provided the most important signals for recognition of ME, whereas best recognition rates for OOM were found in parieto-occipital recordings, overlying visual areas of the cortex. These findings are in line with previous reports showing, for example, activation of visual areas, while subjects observed grasping movements of an 'alien' hand [6].

As concerns the imagery task conditions in our study, only kinesthetic motor imagery, but not visual–motor imagery, resulted in detectable EEG changes. The relevant ERD/ERS patterns, which could be correctly discriminated in 67% of all DSLVQ classifications, were locally restricted to electrodes close to the corresponding sensorimotor hand area. As can be seen in the individual data (Table 1), in half of the investigated subjects (7 out of 14), kinesthetic motor imagery can be recognized (with respect to a resting period) with accuracy close to 70% or higher. It is important to note that these recognition scores are not directly comparable with those obtained related to the detection of imagined movements in the standard BCI literature [22,38,40]. Most of these reports on BCI classification accuracy are based on the cue-based (synchronous) mode of operation. This

implies that, in certain time periods, the classifier has to differentiate between well-defined brain patterns (e.g. right vs. left hand, hand vs. foot movement imagery), which is usually done by analyzing several channels and by extracting several features from each channel. In the present study, we classified 'imagery of movement' versus 'no motor imagery' or 'rest' by considering features of only one channel at a time (channel by channel). The challenge was to distinguish imagery-related patterns from hardly defined EEG patterns during rest.

Altogether, our data show that the same cortical regions that reflect the execution of movement are also indicative for kinesthetic motor imagery. Therewith, further evidence has been provided that motor imagery can activate primary sensorimotor areas, especially when kinesthetic representations are involved. Moreover, our data lend support to the hypothesis that visual and kinesthetic representations of motor actions generate different patterns of cortical activation. There is evidence for a distinct function of visual and kinesthetic imagery from studies investigating the effectiveness of mental practice. Whereas visuomotor imagery is better for tasks that require, e.g. the reproduction of a form by drawing, kinesthetic imagery seems to provide better results for tasks requiring greater motor control (i.e., acquisition of the timing and coordination of movement) [9].

A number of brain imaging studies support the notion that the cortical areas activated during the imagination of a movement correspond very closely to those activated during its performance [6,26,32]. However, despite extensive studies on neural mechanisms of motor imagery, there is still

no consensus as to what degree the primary motor cortex is involved in imagined actions. Whereas some studies failed to detect activation in the primary motor area during motor imagery [3,6–8,12,30], others clearly demonstrated a participation of the primary motor cortex, at least in a part of the investigated subjects [15,16,26,27,32,35]. However, the activation reported is typically not higher than 30% of the activation measured for actual movement execution [26]. Therefore, it is not surprising that in our study the recognition rates for MIK were lower than those for ME.

In order to explain the controversial results in neuroimaging studies, the type of imagery may be important [15]. In some of the studies, it has been reported that subjects primarily visualized hand movements [8], whereas other authors carefully trained the participants to create kinesthetic feelings of moving the limb [15]. A recent study suggests that visuomotor type of imagery may be accompanied by a weak transient response (i.e., initial MRI signal increase) in the primary motor cortex, reflecting the onset of imagination, but not by a sustained activation as obtained during motor execution [7].

In our study, visual–motor imagery, as compared to observation of movement of an animated hand, did not show, overall, a clear contribution of parieto-occipital electrode locations, as could be expected from the literature. As an example, using an integrated visual–motor imagery task (i.e., imagined walking a specific route), Roland and Friberg [31] reported simultaneous brain activation in both visual and higher-order motor cortical regions. Due to the low classification results for the visual–motor task (MIV) in our study, the mental processes associated with this task (i.e., visualization of hand actions) are difficult to interpret. It is not possible to decide whether MIV rather involved somatomotor or visual representations.

Based on inspection of the individual ERD/ERS maps, we can speculate that, in some of the subjects (e.g. p16, see Fig. 1a), MIV, although weaker than MIK, may have involved subliminal activation of the motor system. In others (e.g. ×4, ×8), mainly recordings from parieto-occipital areas show task-related effects. Interestingly, these data displayed enhanced EEG rhythm (ERS) in the alpha and/or beta frequency band. At first glance, this is in contradiction to the general observation that, when a subject concentrates on a particular modality, the EEG activity in the alpha and/or lower beta band specifically decreases in the corresponding brain region [20]. Event-related synchronization (i.e., induced alpha band activity, 10–13 Hz ERS), in contrast, has been interpreted to reflect a state of decreased neural excitability or even inhibited thalamo-cortical circuitry. Future work will be needed to examine the functional significance of parieto-occipital ERS in visual–motor imagery.

Aside from determining the classification accuracy rate (i.e., recognition rate), the rationale of using DSLVQ classification was to weigh the input features (i.e., frequency components recorded at a given electrode position) according to their significance of classification. High weight values show that the corresponding frequency components differ systematically for task-related activity and rest. An advantage of this method, compared with statistical methods based on averaging over trials (such as, e.g. ERD/ERS mapping, [10]), is that DSLVQ weights are not sensitive to absolute values of the input signals nor to the type of reactivity, such as attenuated and enhanced EEG rhythms (ERD/ERS). An interesting outcome of the DSLVQ single-trial analysis was the high relevance of central beta oscillations (16–22 Hz) for movement execution. This finding corresponds to previous studies indicating that cortical neural networks in the primary hand motor area can be characterized by resonance-like frequencies in the range of 16–20 Hz [18]. For recognizing imagery of movement (MIK), upper alpha or mu components (10–12 Hz) are the most relevant features of sensorimotor activity. Higher significance (reactivity) of frequency components in the alpha as compared to the beta range during imagination of finger movement was also reported previously [17]. Regarding the direction of changes of the selected frequencies (i.e., alpha/mu in MIK and beta band components in ME), in all cases, the main contribution comes from an amplitude attenuation or ERD of relevant frequency components. The finding that both observation and visualization of a moving hand affect upper alpha band components in visual cortical areas is consistent with previous studies reporting associations between occipital alpha activity and visual processing [23].

A critical issue of the present study (and many others), where the experimental methodology is based on the instruction to imagine actions, is the fact that the subject's compliance with instruction cannot be assured [1]. The main experimental variation was to ask the participants either to imagine a self-performed action (MIK) or to form mental images (external view) of a previously viewed 'actor' (MIV). The accurate mental performance of the two versions of imagery should be further facilitated by the fact that the two tasks were preceded each by a corresponding 'real' task condition. But, especially the 'alien hand,' instruction in condition MIV may have induced some uncertainty of how to perform this task. Overall, taking together the imagery self-reports and the EEG patterns (i.e., time–frequency maps of ERD/ERS) guided by the timing of the task, the present findings support different processing related to the two imagery conditions. However, it remains impossible to distinguish between subjects who reported vivid imaginations (e.g. kinesthetic feelings of moving the limb) with no identifiable EEG reactivity and participants who may not have followed instructions precisely. Another potential limitation is the lack of simultaneous EMG recordings to exclude muscular activation during imagery. Hence, some weak EMG activity may be present in some subjects during the imagery task. Because there is evidence from previous brain imaging studies that fMRI signal increases during imagery of finger movements do not seem to be related to the degree of EMG activation [26], it is not

very likely that differences in EMG activity apply to our negative findings in MIV. However, additional studies to clarify whether there are systematic differences in EMG activation associated with kinesthetic and visuomotor imagery will be of particular interest.

In summary, the present findings based on DSLVQ classification confirm previous studies that motor imagery can be used to 'produce' (movement-)specific and locally restricted patterns of the oscillatory brain activity, which are detectable in ongoing, not-averaged EEG recordings. However, good recognition rates were solely achieved when the 'imaginer' used the strategy of kinesthetic motor imagery (first-person process), whereas recognition was almost impossible when the participant formed a visual image of another's action (third-person process). Consequently, in motor-imagery-based BCI systems, a careful user training supporting 'real' motor imagery, that is, the kinesthetic instead of the visual form, is essential to improve BCI control.

Acknowledgments

References

[1] J. Annett, Motor imagery: perception or action? Neuropsychologia 33 (11) (1995) 1395–1417.

[2] R. Beisteiner, P. Höllinger, G. Lindinger, W. Lang, A. Berthoz, Mental representations of movements. Brain potentials associated with imagination of hand movements, Electroencephalogr. Clin. Neurophysiol. 96 (1995) 183–193.

[3] F. Binkofski, K. Amunts, K.M. Stephan, S. Posse, T. Schormann, H.J. Freund, K. Zilles, R.J. Seitz, Broca's region subserves imagery of motion: a combined cytoarchitectonic and fMRI study, Hum. Brain Mapp. 11 (2000) 273–285.

[4] E.A. Curran, M.J. Stokes, Learning to control brain activity: a review of the production and control of EEG components for driving brain–computer interface (BCI) systems, Brain Cogn. 51 (2003) 326–336.

[5] J. Decety, D.H. Ingvar, Brain structures participating in mental simulation of motor behaviour: a neuropsychological interpretation, Acta Psychol. 73 (1990) 13–34.

[6] J. Decety, D. Perani, M. Jeannerod, V. Bettinardi, B. Tadardy, R. Woods, J. Mazziotta, F. Fazio, Mapping motor representations with positron emission tomography, Nature 371 (1994) 6498.

[7] P. Dechent, K.D. Merboldt, J. Frahm, Is the human primary motor cortex involved in motor imagery? Cogn. Brain Res. 19 (2) (2004) 138–144.

[8] M.P. Deiber, V. Ibanez, M. Honda, N. Sadato, R. Raman, M. Hallett, Cerebral processes related to visuomotor imagery and generation of simple finger movements studied with positron emission tomography, NeuroImage 7 (1998) 73–85.

[9] Y.A. Fery, Differentiating visual and kinesthetic imagery in mental practice, Can. J. Exp. Psychol. 57 (1) (2003) 1–10.

[10] B. Graimann, J.E. Huggins, S.P. Levine, G. Pfurtscheller, Visualization of significant ERD/ERS patterns in multichannel EEG and ECoG data, Clin. Neurophysiol. 113 (1) (2002) 43–47.

[11] C. Hall, S. Goss, Imagery results in motor learning, in: D. Goodman, R.B. Wilberg, I.M. Franks (Eds.), Differing Perspectives in Motor Learning, Memory and Control, Elsevier, Amsterdam, 1985.

[12] T. Hanakawa, I. Immisch, K. Toma, M.A. Dimyan, P. Van Gelderen, M. Hallett, Functional properties of brain areas associated with motor execution and imagery, J. Neurophysiol. 89 (2003) 989–1002.

[13] M. Jeannerod, V. Frak, Mental imaging of motor activity in humans, Curr. Opin. Neurobiol. 9, 6 (1999) 735–739.

[14] W. Lang, D. Cheyne, P. Hollinger, W. Gerschlager, G. Lindinger, Electric and magnetic fields of the brain accompanying internal simulation of movement, Brain Res. Cogn. Brain Res. 3 (1996) 125–129.

[15] M. Lotze, P. Montoya, M. Erb, E. Hülsmann, H. Flor, U. Klose, N. Birbaumer, W. Grodd, Activation of cortical and cerebellar motor areas during executed and imagined hand movements: an fMRI study, J. Cogn. Neurosci. 11 (1999) 491–501.

[16] D.G. Nair, K.L. Purcott, A. Fuchs, F. Steinberg, J.A.S. Kelso, Cortical and cerebellar activity of the human brain during imagined and executed unimanual and bimanual action sequences: a functional MRI study, Cogn. Brain Res. 15 (2003) 250–260.

[17] C. Neuper, G. Pfurtscheller, Motor imagery and ERD, in: G. Pfurtscheller, F.H. Lopes da Silva (Eds.), Event-related Desynchronization, Revised edition. Handbook. Electroencephalogr. Clin. Neurophysiol., vol. 6, Elsevier, Amsterdam, 1999, pp. 303–325.

[18] C. Neuper, G. Pfurtscheller, Evidence for distinct beta resonance frequencies in human EEG related to specific sensorimotor cortical areas, Clin. Neurophysiol. 112 (11) (2001) 2084–2097.

[19] C. Neuper, A. Schlögl, G. Pfurtscheller, Enhancement of left–right sensorimotor EEG differences during feedback-regulated motor imagery, J. Clin. Neurophysiol. 16 (4) (1999) 373–382.

[20] G. Pfurtscheller, F. Lopes da Silva, Event-related EEG/MEG synchronization and desynchronization: basic principles, Clin. Neurophysiol. 110 (1990) 1842–1857.

[21] G. Pfurtscheller, C. Neuper, Motor imagery activates primary sensorimotor area in humans, Neurosci. Lett. 239 (1997) 65–68.

[22] G. Pfurtscheller, C. Neuper, Motor imagery and direct brain–computer communication, Neural Engineering: Merging Engineering and Neuroscience, Proc. IEEE (Special Issue), vol. 89 (7), 2001, pp. 1123–1134.

[23] G. Pfurtscheller, C. Neuper, W. Mohl, Event-related desynchronization (ERD) during visual processing, Int. J. Psychophysiol. 16 (2–3) (1994) 147–153.

[24] G. Pfurtscheller, C. Neuper, D. Flotzinger, M. Pregenzer, EEG-based discrimination between imagination of right and left hand movement, Electroencephalogr. Clin. Neurophysiol. 103 (5) (1997) 1–10.

[25] G. Pfurtscheller, C. Neuper, C. Brunner, F. Lopes da Silva, Beta rebound after different types of motor imagery in man, Neurosci. Lett. 378 (3) (2005) 156–159.

[26] C.A. Porro, M.P. Francescato, V. Cettolo, M.E. Diamond, P. Baraldi, C. Zuiani, M. Bazzocchi, P.E. di Prampero, Primary motor and sensory cortex activation during motor performance and motor imagery. A functional magnetic resonance study, J. Neurosci. 16 (1996) 7688–7698.

[27] C.A. Porro, V. Cettolo, M.P. Francescato, P. Baraldi, Ipsilateral involvement of primary motor cortex during motor imagery, Eur. J. Neurosci. 12 (2000) 3059–3063.

[28] M. Pregenzer, G. Pfurtscheller, Frequency component selection of an EEG-based brain to computer interface, IEEE Trans. Rehabil. Eng. 7 (4) (1999) 413–419.

[29] M. Pregenzer, G. Pfurtscheller, D. Flotzinger, Automated feature selection with a distinction sensitive learning vector quantizer, Neurocomputing 11 (1) (1996) 19–29.

[30] S.M. Rao, J.R. Binder, P.A. Bandettini, T.A. Hammeke, F.Z. Yetkin, A. Jesmanowicz, L.M. Lisk, G.L. Morris, W.M. Mueller, L.D.

Estkowski, E.C. Wong, V.M. Haughton, J.S. Hyde, Functional magnetic resonance imaging of complex human movements, Neurology 43 (1993) 2311–2318.

[31] P.E. Roland, L. Friberg, Localization of cortical areas activated by thinking, J. Neurophysiol. 53 (1985) 1219–1243.

[32] M. Roth, J. Decety, M. Raybaudi, R. Massarelli, C. Delon-Martin, C. Segebarth, S. Morand, A. Gemignani, M. Decorps, M. Jeannerod, Possible involvement of primary motor cortex in mentally simulated movement. A functional magnetic resonance imaging study, Neuro-Report 7 (1996) 1280–1284.

[33] A. Schlögl, BIOSIG—An open source software library for biomedical signal processing. 2003–2004. Available online: http://BIOSIG.SF. NET <http://biosig.sourceforge.net/>.

[34] K. Sekiyama, Mental and physical movements of hands: kinesthetic information preserved in representational systems, Jpn. Psychol. Res. 25 (1982) 95–102.

[35] A. Solodkin, P. Hlustik, E. Chen, S.L. Small, Fine modulation in network activation during motor execution and motor imagery, Cereb. Cortex 14 (2004) 1246–1255.

[36] J.A. Stevens, Interference effects demonstrate distinct roles for visual and motor imagery during the mental representation of human action, Cognition 95 (3) (2005) 329–350.

[37] P. Suffczynski, P.J.M. Pijn, G. Pfurtscheller, F.H. Lopes da Silva, Event-related dynamics of alpha band rhythms: a neuronal network model of focal ERD/surround ERS, in: G. Pfurtscheller, F.H. Lopes da Silva (Eds.), Event-related Desynchronization, Revised edition. Handbook. Electroencephalogr. Clin. Neurophysiol., vol. 6, Elsevier, Amsterdam, 1999, pp. 67–85.

[38] T. Wang, H. Deng, B. He, Classifying EEG-based motor imagery tasks by means of time–frequency synthesized spatial patterns, Clin. Neurophysiol. 115 (12) (2004) 2744–2753.

[39] T. Weiss, E. Hansen, R. Rost, L. Beyer, F. Merten, C. Nichelmann, C. Zippel, Mental practice of motor skills used in poststroke rehabilitation has own effects on central nervous system activation, Int. J. Neurosci. 78 (1994) 157–166.

[40] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, Brain—Computer interfaces for communication and control, Clin. Neurophysiol. 113, 6 (2002) 767–791.