Freie Universität Berlin
Fachbereich Erziehungswissenschaft und Psychologie
Diplomstudiengang Psychologie
Arbeitsbereich Neurokognitive Psychologie

Charité Universitätsmedizin Berlin
Campus Benjamin Franklin
Klinik und Hochschulambulanz für Neurologie und Klinische Neurophysiologie
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Friederike U. Hohlefeld

Freie Universität Berlin

Introducing quasi-movements:

An EEG/EMG study with special emphasis on brain-computer interface application

Erstgutachter:	Prof. Dr. Arthur M. Jacobs (FU)
Zweitgutachter:	Prof. Dr. Gabriel Curio (CBF)
Mentor:	Dr. Vadim V. Nikulin (CBF)

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Introducing quasi-movements:
An EEG/EMG study with special emphasis on brain-computer interface application

Friederike U. Hohlefeld (2006)
Free University Berlin

Abstract

Can you do a movement without doing it? The present study provides multiple lines of evidence for the performance of movements without their overt execution: Quasi-movements are defined as movement execution with infinitively minimized or completely reduced movement force, resulting in subliminal or absent motor output measurable by EMG. They provide a novel behavioral paradigm which is neither actual movement execution nor (kinesthetic) motor imagery. Our study examines these three experimental conditions in a phasic thumb movement task in terms of EMG, oscillatory neuronal activity (8–13 Hz), EEG single-trial classification, and psychological testing. Our results demonstrate that quasi-movements are intended as genuine motor actions, but their subjective experience resembles motor imagery. The spatial distribution of electrophysiological activity did not differ significantly between the three conditions, but it was clearly modulated in its strength, as reflected by stronger event-related desynchronization compared to motor imagery. Quasi-movements are performed with practically zero-force and therefore are suitable for application within a brain-computer-interface. Classification accuracy could be improved by approximately 50–80% compared to motor imagery. Quasi-movements are of practical relevance for neurophysiology, neurocognitive psychology, and computational neuroscience, and their paradoxical nature is only resolvable by interdisciplinary combination of these fields.

Keywords: abductor pollicis brevis; alpha; amputees; APB; BCI, brain-computer interface, CSP, common spatial patterns; EEG, EMG, ERD, event-related desynchronization, feedback, human; inhibition; intention; machine learning; minimization; motor control; motor cortex; motor imagery; movement execution; mu rhythm; paralyzed; imagery questionnaire; quasi-movements; sense of movement; single-trial analysis; spontaneous oscillations.

E-mail: F.U.Hohlefeld@web.de

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Abbreviations

BCI	brain computer interface
CSP	common spatial pattern
EEG	electroencephalography/-gram
EMG	electromyography/-gram
ERD	event-related desynchronization
QMI	questionnaire upon mental imagery
RMS	root-mean-square
TMS	transcranial magnetic stimulation
VMIQ	vividness of motor imagery questionnaire

I. INTRODUCTION

1.1 Brain-computer interface (BCI) research

Consider yourself sitting in front of your computer, hands lying completely relaxed on your lap. You are wearing a somewhat unusual cap with electrodes, which is connected to the computer. On the screen you see a cursor, which is movable in right and left direction. Consider now the possibility how to move this cursor without touching the mouse or using the keyboard. One way is simply to imagine moving your left or right hand, respectively. The cursor moves faster and more accurate, the stronger you are able to modulate your brain activity, which the computer analyzes in order to extract a command signal for the software application, which you are controlling by a so-called "brain-computer interface" (BCI).

"BCI research is an interdisciplinary endeavor…. [and] involves neurobiology, psychology, engineering, applied mathematics, and computer science. Success depends on expertise in all these disciplines and on effective interactions between them" (Wolpaw, Birbaumer, McFarland, Pfurtscheller & Vaughan, 2002, p. 784). It is a special field in the study and development of brain-machine interfaces, whose main characteristics and challenges are outlined by Nicolelis (2001) or by Donoghue (2002).

A BCI provides a communication channel between the (human) brain and the computer, which does not rely on the "usual" output pathways of nervous and muscular activity in the interaction with the computer, thus bypassing the usage of mouse, keyboard, speech, and the like (Wolpaw et al., 2002). It allows the control of and communication via mechanical and electronic devices for non-disabled users and especially for users with severe neuromuscular disabilities, like patients with amyotrophic lateral sclerosis, spinal cord lesions or subcortical stroke, resulting in locked-in states or complete paralysis. These artificial devices include for example the control of neuroprostheses for persons with amputations, wheelchairs or multimedia applications (cursor-moving, text spelling, web browsing, (still) simple computer games, walking in virtual environments). Broadly speaking, the user's "intentions", "thoughts" or "imaginations", as reflected by associated changes of spontaneous or evoked electric brain activity, are translated into a technical command signal (Birbaumer et al., 1999; Krepki, Blankertz, Curio, & Müller, 2003; Kübler, Kotchoubey, Kaiser, Wolpaw, & Birbaumer, 2001; Müller-Putz, Scherer, Pfurtscheller, & Rupp, 2005; Pfurtscheller, Leeb, Keinrath, Friedman, Neuper, Guger, & Slater, 2006; Wolpaw et al., 2002). Ideally, these brain signals should not be created by peripheral processes, but only by the internally modulated neuronal activity. The main challenge is how to effectively (learn to) control one's own brain activity in order to obtain a reliable and efficient command signal for the given device. In this respect, motor imagery has been found to be the most adequate strategy (Birbaumer, 2006; Neuper, Scherer, Reiner, & Pfurtscheller, 2005). For example, motor imagery of specific hand, foot or even tongue movements generate specific neuronal activity detectable by electroencephalography (EEG). Voluntary modulation of the amplitude of (sensorimotor) mu rhythms as well as of central beta rhythms by motor imagery is documented comprehensively in BCI research (Pfurtscheller, Brunner, Schlögl, & Lopes da Silva, 2006; Neuper et al., 2005).

A BCI system consists generally of three components: a) the user, producing the neurophysiological command signal, b) the interface (like amplifiers, PC, analysis software, monitor etc.) which processes, filters, and presents the obtained raw data in such a way, that c) the selected application is possible. In this setup the user has to perform two tasks simultaneously: firstly following the appropriate (mental) strategy to achieve control over his neurophysiological activity, and secondly interacting with the artificial device or multimedia application itself via usually visual feedback.

A variety of ways to use neurophysiological signals derived from brain activity are available for BCI systems; accordingly, BCIs are distinguished by two main types, non-invasive and invasive systems. “Invasive BCIs use activity recorded by brain implanted micro- or macro-electrodes, whereas non-invasive BCIs use brain signals recorded with sensors outside the body boundaries” (Birbaumer, 2006, p. 517). Invasive systems use data obtained by electrocorticograms or from neuronal action potentials (from single neurons or from nerve fibers). Non-invasive BCIs can be based on multichannel surface EEG, using event-related potentials (like P300 or slow cortical potentials) or changes in spontaneous brain oscillations as reflected in event-related desynchronization/synchronization (ERD/S; e.g. in the mu/alpha or beta frequency range). Other available BCI systems are based on magnetoencephalography, functional magnetic resonance imaging or on near-infrared spectroscopy, whereby EEG is the most common technique in usage (Blankertz, Schäfer, Dornhege, & Curio, 2002; Birbaumer, 2006; Kauhanen, Nykopp, & Sams, 2006; Kübler et al., 2001; Nicolelis, 2001; Wolpaw et al., 2002). In general, BCIs can be paced (cued or synchronous BCI) or self-paced (uncued or asynchronous BCI). In either case, the main challenge is to discriminate between the obtained brain signals with respect to the user’s “intention”, for instance differentiate between “intended” right or left movements. A variety of pattern recognition methods is available for this classification, which can broadly divided in linear approaches (like e. g. linear discriminant analysis) and nonlinear approaches (like artificial neural networks), whereby preprocessing of the signal is as important as the “training” of the so-called classifiers itself (Blankertz et al., 2002; Müller, Anderson, & Birch, 2003). Faced with the immense (and still growing) variety of possible feature extraction methods it is “agreed that simplicity is generally best” (Müller et al., 2003, p. 169).

Operating with a BCI system requires training, describable as both user and interface “adapting to each other”. One possibility is teaching the *user* via biofeedback, operant conditioning and/or self-regulation techniques, which needs long training periods of some weeks or even months (Birbaumer, 2006; Hinterberger et al., 2004; Kübler et al., 2001). The other possibility is teaching the *computer* (“Let the machines learn!”, Krepki et al., 2003, p. 240) to adjust to the user’s produced bio signal’s characteristics. This mainly automatic procedure (based on single trial analysis) can efficiently shorten training periods (offline) to 30 minutes and allows immediate subsequent online feedback; the main approach of the Berlin Brain-Computer Interface (BBCI; Blankertz, Dornhege, Krauledat, Müller, Kunzmann, Losch, & Curio, 2006; Shenoy, Krauledat, Blankertz, Rao, & Müller, 2006; cf. http://www.bbci.de and http://ida.first.fraunhofer.de/homepages/ida/ [27.11.2006]).

The last step is to get from offline machine training to the complex online feedback situation in which the user operates the interface in real-time. EEG signals are recorded with simultaneous EMG and EOG in order to select artifact-free trials for classification, so that classification is based mainly on cognitive responses, and is not biased by peripheral activity. Absence of peripheral artifacts is the prerequisite for evaluation criteria like information transfer speed of the communication or the accuracy of the brain-computer interaction (Kübler et al., 2001). These criteria which characterize the user’s performance are influenced by three main factors: technical, neurophysiological, and psychological.

Technical factors in a BCI system comprise processes which are rather independent from the user, like recording technology or analysis procedures. Individual neurophysiological characteristics of the user provide the basis for establishing a communication channel between computer and brain. Last but not least, the neurophysiological production of a command signal can be influenced strongly by psychological factors, like the chosen mental strategy, given task instructions, motivation, previous imagery training or BCI-experience, and experienced success or frustration/stress in the online feedback-situation. The average BCI user can elicit quite stable and distinctive EEG patterns, resulting in a moderate or satisfactory communication with/via the BCI in terms of the so-called classification error or bits per minute (e.g. possible information transfer rates of up to 35 bits/minute; Wolpaw et al., 2002; Shenoy et al., 2006).

1.2 BCI and motor imagery

As already mentioned above, studies in BCI context demonstrate that motor imagery modulates the amount, temporal and spatial characteristics of neuronal activity to different extents. So-called “kinesthetic” motor imagery requires to “feel” own movements from an internal, first-person perspective (egocentric); that is, to perceive the muscle activity corresponding to the actual execution of the imagined movement. Kinesthetic motor imagery (MIK) can be conceived as “neurally simulated actions” (Jeannerod, 2001, p. 103). Visual motor imagery requires the visualization of one’s own movement from an external, self-allocentric view, thus using the third-person perspective (Guillot & Collet, 2005; Hall & Martin, 1997; Isaac, Marks, & Russell, 1986; Jeannerod, 1994; Möller, 2004; Solodkin, Hlustik, Chen, & Small, 2004; Stinear, Byblow, Steyvers, Levin, & Swinnen, 2006). That is, as if one is watching *oneself* performing a movement (like in a movie). It should not be confounded with *visual* imagery of movements in general (with third-person perspective, like watching *somebody else* doing a movement). Choosing *kinesthetic* motor imagery as mental strategy to operate a BCI has been found advantageous compared to other imagery strategies like *visual* motor imagery, resulting in better discrimination of electrophysiological activation patterns (Neuper et al., 2005).

1.3 BCI, motor imagery, and failures in brain-computer interaction

Consider yourself trying to move the cursor by imaging left or right hand movements. And despite desperate attempts the cursor keeps on moving uncontrolled in either direction, or does not move at all.

Despite fast developments in BCI technology and application of adequate mental strategies, neuronal signals cannot be modulated with the same efficiency in all users. Studies consistently report a number of individuals (without or with motor disabilities) not being able to achieve sufficient classification rates, resulting in unsatisfactory performance during online brain-computer interaction (McFarland, Sarnacki, Vaughan, & Wolpaw, 2005; Neuper et al., 2005). It can be assumed that this is due to neurophysiological/psychological reasons mentioned above, because: if the user cannot modulate his/her brain activity to the necessary extent, then even the best machine learning algorithm has no signal to detect.

Solutions to this problem might work on different levels:

a) Technical progress on the long-term perspective or using invasive BCI with better signal to noise-ratio;

b) introduce special training of motor imagery abilities, relaxation techniques, or expand training of the interaction with the BCI system;

c) invent an alternative strategy to motor imagery that produces a stronger modulation of neuronal activity.

1.4 Quasi-movements

Perform the abduction of your thumb and let this movement be relatively weak. Now try to minimize this small movement even further and make your movements as small as it is possible for you.

So far, no satisfactory solution for the portrayed problem situation of poor BCI performance during motor imagery has been found. In contrast to prevailing motor imagery strategies we propose an experimental paradigm that introduces a simple and effective behavioral motor task providing a more robust command signal. The instruction above describes its basic idea: to reduce one's motor execution strength to such an extent that the movement is not executed anymore. We call this type of motor performance "quasi-movement".

Quasi-movements are defined as movement execution with infinitively minimized or completely reduced movement force, resulting in subliminal or absent motor output measurable by EMG. They constitute a paradoxical dual-task situation, namely the performance of a movement without its (overt) execution.

"Motor output" is defined on the basis of EMG measurement of the respective muscle(s) involved in the given movement. Absent motor output indicates muscle activity that is undistinguishable from baseline activity during rest; subliminal motor output are muscle responses clearly distinguishable within or barely above baseline activity, as compared to the actual movement execution.

Our study provides neurophysiological and psychological evidence for the initial hypotheses

1) that the performance of such a paradoxical task like the performance of quasi-movements is possible while having characteristics distinct from "pure" motor imagery and actual movement execution;

2) quasi-movements fulfill the *objective* criteria applied to common definitions of motor imagery, namely none or sometimes very weak muscular activity, obtained by EMG;

3) yet they differ in one critical aspect from the former: quasi-movements are derived from, intended and performed as “real” motor execution, respectively;

4) but still, their *subjective* experience resembles (kinesthetic) motor imagery more than actual movement execution, as operationalized by semantic evaluation of the task and rating of proprioceptive sensations during task performance;

5) the electrophysiological brain activity during the performance of quasi-movements (as obtained by EEG) resembles imagined and executed movements in terms of spatial distribution, but differs in the activation strength;

6) the performance of quasi-movements improves classification accuracy for electrophysiological patterns, especially for subjects with comparably poor classification results when using imagery strategies; furthermore:

7) the results of the present study are consistent with common findings in motor imagery research which suggest a continuous transition between motor imagery and movement execution;

8) quasi-movements provide an alternative paradigm to motor imagery to study motor behavior in non-disabled subjects without being confounded by presence of muscle activity or peripheral feedback, respectively, with implications for the generalizability of results to patients with motor impairments in the context of BCI application.

II. PROCEDURE

2.1 Subjects

17 non-disabled subjects (mean age 29 years, range 19–48 years, *SD* = 6.8; 9 males, 8 females) without history of neurological or psychiatric disorders participated in the present study and were recruited from the student or staff population of Free University Berlin and Charité Berlin without payment for their participation. All subjects had normal or corrected-to-normal vision. 13 of them were right-handed according to the Edinburgh Handedness Inventory (Oldfield, 1971). Five subjects were not native German speakers; in this case, English versions of the instructions and all questionnaires were provided. Six subjects (including the author) had prior experience with BCI feedback. All subjects understood completely the nature of the experimental procedures and provided informed consent prior to participation. Experimental procedures were approved by the Ethics Committee of Charité University Medicine Berlin, Berlin, Germany.

2.2 Experimental conditions

Prior to any measurements the subjects were informed about the main procedure and purpose of the experiment, without explaining the nature of the required tasks in order to avoid expectation bias. The experimental conditions of the present study required the performance of three different tasks: movement execution, kinesthetic motor imagery, and quasi-movements, referred to as "real", "imag", and "quasi", respectively. The type of movement for these tasks was the abduction of the left or right thumb with the respective abductor pollicis brevis. This muscle was chosen because it is a flat and superficially located; therefore even smallest activation of it is easily detectable since the contracting muscle fibers are close to the recording electrode.

Stimuli

The subjects were sitting in a comfortable armchair, facing a centered computer screen (43 cm in diagonal) at a distance of approximately 50 cm. Their hands were positioned in a maximal relaxed position, which could change across subjects and within experiment conduction.

The performance of all three tasks was cued by visual stimuli presented on the computer screen. Visual stimuli were the black letters "L" and "R" (4.2 x 3 cm) with the visual angle (4.8° x 3.4°) on grey background, referring to left and right movements, respectively. Accordingly, the stimuli will also be referred to as left and right (movement) class. Stimulus duration was 3 ± 0.2 seconds '(in four subjects this interval was 2 ± 0.2). The inter-stimulus interval varied randomly in the range of 2.75 ± 0.5 seconds (in four subjects this interval was 1.75 ± 0.5 seconds). The order of the stimulus presentation was randomly distributed and the same stimulus was never presented more than three times in a row. The duration of one recording session was approximately 12 minutes, with an initial 30-seconds relaxation period and two intermediate 30-seconds breaks. Each session comprised a total number or 108 stimuli (54 "L" and 54 "R" stimuli for left and right class, respectively). Each of the three tasks consisted of two sessions. The session order was random and the same task condition was never recorded directly after another, apart from the first seven subjects the session order was fixed ("imag", "quasi", "real").

Task instructions

In "real" task the subjects were supposed to perform approximately six quick, continuous thumb abductions, depending on whether "L" or "R" was presented, respectively. Subjects were instructed to produce weak but clearly visible movements which should be stopped immediately when the stimulus disappeared from the screen. The other hand should be relaxed completely during this movement, as well as both hands in between trials.

In "imagery" task the subjects were asked to imagine the described thumb movement with the same strength and frequency. The task required kinesthetic motor imagery of the movement (from an internal, first-person perspective) and the subjects were explicitly instructed to neither visualize its performance nor to imagine tactile aspects or to internally count the movement. The hands should be kept completely relaxed during and in between the trials.

The main idea of the "quasi" task was to train subjects performing the movement from "real" condition but with response strength undetectable by EMG, thus being not distinguishable from the performance in "imagery" condition. Therefore, the subjects were instructed in the first place to execute very weak thumb abductions. In successive trials, the subjects had to diminish the strength of that movement as far as possible, that is, reducing their muscle activity to a minimum. To achieve that state, the subjects received a training of varying length (about 15 minutes) before the start of the recording. The training consisted of two phases: visual feedback and then only verbal feedback. First, the subjects were shown their own EMG traces on the monitor in front of them. They were instructed to reduce amplitude peaks of thumb movements in a self-paced manner, producing EMG activation barely above (pre-stimulus) baseline activity. It is important to note that at this stage mere visual detection of thumb movements was impossible; therefore it was critical to inform subjects that although they might not feel or see their movements, it still could be registered with EMG. When subjects reported that they feel like they were able to perform the task, and they succeeded in execution of thumb abduction with an EMG amplitude of approximately 7–10 µV, they received a training in movement strength reduction with only verbal feedback by the researcher. The researcher watched EMG activity while instructing the subjects to do left or right thumb movements. If the movement strength exceeded baseline level, the subject was informed to reduce movement strength. This was a crucial moment in the training of quasi-movements, because subjects were trained to minimize already tiny movements to the point when they were practically not executed anymore (as viewed by the researcher). Certainly this fact had to be concealed from the subjects in order to prevent them from thinking that the movement has not been actually performed. And exactly for this reason the subjects were not shown their EMG traces in the second training phase but received only verbal feedback. During the training and recording of "quasi" condition, the EMG traces were watched carefully in order to detect (weak) motor responses. They were defined as such if the amplitude clearly exceeded (pre-stimulus) baseline level. During observation, the resolution was kept at 20 µV. For concrete task instructions for all three conditions see Appendix A.

2.3 Questionnaires

Prior to starting any recordings or explaining the nature of the upcoming task conditions, we were interested in the subject's initial, general understanding of the term "imagination". Therefore, we asked them to select three words from a list of expressions a) related to "imagination" and b) semantically opposite to this term.

In addition to the behavioral performance of the three described motor tasks, the subjects were supposed to rate and evaluate their performance for "imag", "quasi", and "real" conditions. First, they were asked to rate to what extent their subjective experience of each task's performance belonged to "real" or "imagery" category. Therefore, they put a mark on a solid line connecting these two words as poles of a continuum ("reality index"). The subjects also evaluated their proprioceptive sensations related to the task performance on a discrete scale consisting of five units with "1" corresponding to the weakest and "5" to the strongest sensation, respectively. For "quasi" condition they were supposed to rate the amount of movement strength with which they performed quasi-movements, by putting a mark on a continuous line connecting the words "min" and "max", with the former corresponding to almost no strength at all. These three ratings were given after completion of the second recording session of the respective condition.

Second, the subjects ranked the tasks according to the subjective amount of effort and concentration, that is, as how demanding the task was experienced. Moreover, the tasks were ranked in ascending order of how "real" they were perceived. These ratings were given after completion of all session recordings (cf. Appendix B).

Third, after finishing the experiment the subjects were handed two standard psychological questionnaires for general imagery abilities: the Questionnaire Upon Mental Imagery (QMI; the shortened version, cf. Sheehan, 1967, reprinted in Richardson, 1969) and the Vividness of Movement Imagery Questionnaire (VMIQ; Isaac et al., 1986). Both instruments aim at the assessment of the "vividness" (clarity or sensory "richness"; Moran, 1993) of the experienced (motor) image elicited by the respective item. Lower ratings indicate higher imagery ability. The QMI assesses the vividness of mental imagery in seven modalities (visual, auditory, cutaneous, kinesthetic, gustatory, olfactory, organic) on a 7-point Likert-scale. Each modality contains five items which are imagined with eyes open. The VMIQ assesses the vividness of motor imagery for different types of movements in six categories ranging from simple to complex body movements. Each category consists of five items, rated with eyes closed, on by a 5-point Likert-scale. The VMIQ comprises two subscales referring to external (third-person perspective) and internal (first-person perspective) motor imagery, respectively. The scores for these imagery ability questionnaires were calculated as mean scores across items. Scores for the QMI were calculated across all imagery modality subscales. For the VMIQ the individual mean score was calculated across all items separately for the kinesthetic motor imagery subscale, because "imag" task incorporated explicitly imagery of kinesthetic sensations from first-person perspective only (cf. Appendix C for items and rating scales of both questionnaires).

III. METHODS

3.1 EEG and EMG recordings

Surface EEG was recorded with 120 electrodes placed according to the extended International 10-20 system (Jasper, 1958) referenced to nasion; the electrodes having a diameter of approximately 12 mm and an inter-electrode distance of approximately 1.5–2 cm (BrainCap; Brain Products GmbH, Munich, Germany). Surface EMG was recorded in a bipolar montage from left and right abductor pollicis brevis (compare Appendix E Figure A1; Bischoff, Dengler, & Hopf, 2003) with one electrode located over the muscle belly and the other over the proximal base of the phalanges. Prior to electrode attachment (sintered Ag/AgCl ring electrodes) the skin was prepared according to standard methods to reduce skin impedance (Picton, Bentin, Berg, Donchin, Hillyard, Johnson, et al., 2000). Vertical and horizontal electrooculogram was also recorded to control eye-movement artifacts during data acquisition. Impedances were kept below 50 kΩ.

Data were recorded with using BrainAmp amplifier (BrainAmp MR plus, input noise <1 μVpp) with 16 bit A/D converter (0.1 μV accuracy) and *BrainVision Recorder* software (version 1.03, Brain Products GmbH, Munich, Germany), and stored for later analysis.

For analysis of EEG recordings the most anterior, posterior, and temporally located electrodes were excluded since they contained high amount of muscle activity, reducing the total number of channels to 86. During acquisition of EEG and EMG data the signals were band-pass filtered with 0.1–250 Hz frequency band and digitized with a sampling frequency of 1000 Hz. For the following offline analysis EEG data was down-sampled offline to 200 Hz (by picking up each 5th sample); EMG data was high-pass filtered at 10 Hz, band-stop (notch) filtered at 50 Hz, and rectified.

3.2 EEG analysis

Preprocessing

EEG data was segmented into epochs consisting of 1000 ms pre-stimulus activity and 5000 ms post-stimulus activity, respectively, and analyzed for the presence of outliers in order to obtain artifact-free epochs for further analysis. Therefore, two complementary methods were applied. The variances from all channels for a given epoch were averaged, thus resulting in one value for each epoch. Then these values were sorted in an ascending order. If a clear discontinuity was visually determined among sorted values, the epochs lying above this discontinuity were discarded from the analysis. The second method calculates the Mahalanobis distance for each epoch (also on the basis of variances) as a measure of its similarity with the rest of the epochs. Then the sorting and exclusion of epochs was performed as described above. Since the first method is sensitive to absolute deviations and the second to the deviations from a common structure, the combination of both methods provides an effective approach for the selection of noise-free epochs. Then EEG data was analyzed in two parts, as described below.

Modulation of ongoing oscillatory activity in the alpha range

In the first part of the analysis for all three conditions, EEG data was re-referenced using the small Laplacian method, based on the subtraction of averaged activity of four neighboring electrodes from the activity in the given electrode (Hjorth, 1975; Graimann & Pfurtscheller, 2006). In order to evaluate a degree of cortical activation related to the experimental tasks, we based our analysis on previous findings demonstrating that event-related desynchronization (ERD) of spontaneous oscillatory neuronal activity in the alpha frequency band represents "electrophysiological correlate[s] of activated cortical areas involved in processing of sensory or cognitive information or producing of motor behavior" (Pfurtscheller & Lopes da Silva, 1999, p. 1852; cf. also Berger, 1929; Foucher, Otzenberger, & Gounot, 2004; Hanslmayr, Sauseng, Doppelmayr, Schabus, & Klimesch, 2005; Klimesch, Schack, & Sauseng, 2005; Linkenkaer-Hansen, Nikulin, Palva, Ilmoniemi, & Palva, 2004; Pfurtscheller et al., 2006; Neuper et al., 2005; Nikouline et al., 2000; Nikouline, Wikström, Linkenkaer-Hansen, Kesäniemi, Ilmoniemi, & Huttunen, 2000; Nunez, Wingeier, & Silberstein, 2001). ERD describes "the event-related, short-lasting and localized amplitude *attenuation* of EEG rhythms within the alpha or beta band" and event-related synchronization (ERS) "describes the event-related, short-lasting and localized *enhancement* of these rhythms" (Kalcher & Pfurtscheller, 1994, p. 381; italics added). "This means that these event-related phenomena represent frequency specific changes of the ongoing EEG activity and may consist, in general terms, either of decreases or of increases of power in given frequency bands… [which] may be due to a decrease or increase in synchrony of the underlying neuronal populations, respectively" (Pfurtscheller & Lopes da Silva, 1999, p. 1842). ERD is defined as the percentage of band power decrease in post-stimulus interval compared to referential pre-stimulus interval values (Kalcher & Pfurtscheller, 1994; Pfurtscheller & Aranibar, 1977; Pfurtscheller & Lopes da Silva, 1999).

After Laplacian transform the activity in each channel was filtered in the 8-13 Hz frequency range. In order to obtain an amplitude envelope of alpha oscillations the Hilbert transform was applied (Clochon, Fontbonne, Lebrun, & Etevenon, 1996; Graimann & Pfurtscheller, 2006; Rosenblum & Kurths, 1998). Then EEG data was averaged across epochs separately for each stimulus class (“L” or “R”). Using average traces of the amplitude dynamics of the alpha oscillations, ERD was calculated for each channel as (POST-PRE)/PRE, where POST is the averaged activity in post-stimulus interval (70–3330 ms) and PRE is the averaged activity in pre-stimulus interval (-500–0 ms). For each movement class the electrode with strongest ERD was selected separately for left and right sensorimotor areas.

Single trial EEG classification

In the second part of the analysis for all three conditions, single EEG epochs were classified depending on whether the subject was performing (or imagining) left or right hand (thumb) movements (actual execution or quasi-movements). This contrast of left vs. right movements is crucial for capturing the brain activity related primarily to motor (imagery) components, while the rest of the activity, related to general factors such as attention or arousal level, should be similar for both movement classes and thus not significantly affect obtained contrasted EEG activity. In order to obtain an optimal discrimination of EEG activity belonging to two classes, an automatic procedure for selection of frequency band, time interval and spatial EEG structures is described below.

First the (Laplacian re-referenced) EEG data was filtered in the broad frequency range from 7–30 Hz, where one would expect major reactivity in the three conditions. The amplitude envelope of oscillations was obtained with the Hilbert transform. Then an iterative procedure was applied to find what post-stimulus interval discriminates mostly between left and right class. For this purpose we used point-biserial correlation, a measure which gives the strength of the relation between a continuous variable (here the mean amplitude of EEG in post-stimulus interval) and a binary variable (-1 and 1 like for left and right movement class).
The time points with the strongest correlations in the post-stimulus interval were selected with the criteria of encompassing 80% of the largest correlation values. The time interval determined in this way was then used for the selection of a frequency band with optimal discrimination between both classes. For this purpose the spectral power (based on Fast Fourier Transform) was computed for each epoch in the already determined time interval, and the point-biserial correlation was calculated between each frequency bin and the binary class variable. The neighboring frequency bins with the strongest correlations were selected to form an optimal frequency band (opt_band) for discriminating between the two classes. The low and upper limits of opt_band were defined on the basis of point-biserial correlation not being smaller than 1/3 of the highest correlation in the center of opt_band. Then again an optimal

time interval (opt_ival) was determined for discrimination between two classes, but now using the frequency band found above. After selection of the optimal frequency band and post-stimulus interval, spatial filtering was performed for the class-wise separation of EEG data. Therefore, the originally recorded data (nose-referenced) was band-pass filtered using opt_band and the epochs were created in the time interval opt_ival. Using all available channels, the EEG segments were analyzed by common spatial patterns (CSP) method (Fukunaga, 1990; Koles, Lind, & Soong, 1995; Müller-Gerking, Pfurtscheller, & Flyvbjerg, 1999; Pfurtscheller & Graimann, 2006). The main idea behind CSP analysis is to determine spatial filters that maximize variance in one class while at the same time minimizing the variance in another class. For band-pass filtered EEG signals variance is equal to power in a given frequency range; therefore, spatial filters reflect contrast between the classes with respect to the strength of ERD/ERS. CSP analysis has been successfully applied for EEG single trial classification for BCI purposes (Blankertz, Dornhege, Krauledat, Müller, & Curio, 2005; Dornhege, Blankertz, & Curio, 2003), and it provides an optimal linear combination of channels for best discrimination between the given two classes, thus being "reference-free". Accordingly, the algorithm gives a spatial filter matrix decomposing EEG data into optimal components, whereby its inverse allows the visualization of activation patterns, similar to the relationship between de-mixing and mixing matrices utilized for independent component analysis.

Although CSP analysis provides as many spatial filters as there are channels in EEG matrix, we selected only four filters (patterns; two for each of the classes) with the largest eigenvalues. Increasing the number of filters usually does not lead to increased discriminability between classes. After these four CSP filters were obtained, they were used for spatial filtering of EEG data (that had been already filtered in time domain with opt_band). Multiplication of the given filter matrix with the data matrix resulted in a matrix t x 4 x N, where t is length of opt_ival and N is the number of epochs for both left and right movement classes. Then the logarithm of variance was calculated for each epoch, for achieving close to-normal distribution of the data. This procedure finally led to a 4xN matrix, which was used for classification. In order to see how the two classes can be separated in the present four-dimensional space, we used linear discriminant analysis (e.g., Blankertz et al., 2005; Friedman, 1989; Nikouline, Ilmoniemi, & Kulikov, 1999; Shenoy et al., 2006). After that cross-validation was performed for establishing the classifier's robustness. The main idea of this procedure is to use one part of the data set for classifier training, and another part for verifying how the classifier can be generalized to the data not used in the training. The

training procedure consists of finding CSP filters and coefficients from linear discriminant analysis only on the basis of the training set, whereby opt_band and opt_ival remain unchanged. For the present study we divided the data into eight training sets in non-overlapping chronological order, and the classifier was trained on 7/8 of the total number of epochs while testing it on the remaining 1/8. In each of these iterations the number of misclassified epochs (divided by the number of all classified epochs) is referred to as classification error, and the average of these errors is the average cross-validation classification error, which we will report.
This procedure, as described above, is a standard signal processing routine which is used in the Berlin Brain-Computer Interface project (BBCI). Please refer to Blankertz, Dornhege, Lemm, Krauledat, Curio, and Müller (2006) for more technical details. In addition to classifying single EEG trials for BCI purposes, it represents a powerful tool for the selection of spectral, temporal, and spatial aspects of neuronal activity related to movement execution or motor imagery (and quasi-movements).

Similarity between spatial activation patterns

As mentioned above, the inverse of the filters obtained by common spatial pattern analysis results in an activation (mixing) matrix reflecting cortical activity. Another interest of the present study was to quantify the degree of similarity between spatial activation patterns across conditions. For each of the two obtained CSP and for each class we determined a “similarity index” between corresponding activation patterns of two conditions (“quasi” vs. “imag”, “quasi” vs. “real”, “real” vs. “imag”). The “similarity index” was calculated as the absolute value of a cosine of an angle between two CSPs in an E-dimensional space, where E is the total number of channels. It varies from 0 to 1, with 1 corresponding to completely similar patterns and 0 to completely dissimilar patterns.

3.3 EMG analysis

The analysis of EMG data was also conducted in two parts. The main steps were first the detection of muscle activity related to motor performance in the three conditions, and second the comparison of pre- and post-stimulus activity in “silent” EMG trials which did not contain visually detectable motor responses.

Detection of (weak) motor responses

Motor responses ("EMG onset") are considered as phasic muscle contractions related to the presented stimulus for a specific task. Their amplitudes clearly exceed pre-stimulus baseline muscle activity present at rest; "imag" and "quasi" tasks can sometimes even comprise response patterns within the amplitude level of baseline activity (but being clearly distinct from it). The identification of motor responses can be achieved by two procedure types: visual inspection by the researcher and a variety of automatic (computer-based) analysis (Abbink, van der Bilt, & van der Glas, 1998; Hodges & Bui, 1996; Reaz, Hussain, & Mohd-Yasin, 2006). In our study, with "imag", "quasi", and "real" tasks three different types of motor responses needed to be properly analyzed, whereby the latter being comparably easy to detect. In case of "imag" and "quasi" condition, things become much more complicated. Ideally, motor imagery should not involve any motor output, but it has been found to be accompanied to a certain extent by subliminal muscular activity (Guillot & Collet, 2005; Jacobson, 1932; Shaw, 1938). The challenge for quasi-movements is to identify motor responses which "escaped" the subject's effort to reduce movement strength to the stage of absent motor output. These motor responses are of unknown exact onset latency, extremely short duration, fast frequency, and of very weak amplitude (in the latter case also easily confoundable with residual electrocardiogram). An algorithm for the reliable identification of these characteristics in this novel type of EMG activity has not been proposed so far. Therefore we selected visual inspection as strategy to determine presence and characteristics of motor responses.

Prior to visual inspection, EMG data was segmented into epochs with time intervals from -2000 to 3300 ms with respect to the stimulus. Left hand EMG traces sometimes contained residual electrocardiogram; these artifacts were decreased by applying independent component analysis (fastICA; Hyvärinen & Oja, 2000), with curtosis as a contrast function.

EMG epochs containing excessive amount of background muscle activity (or technical artifacts) were excluded from the analysis since they comprise the detection of weak motor responses. EMG traces were visually inspected epoch by epoch for left and right hand separately in order to determine motor responses in pre-stimulus interval (-1000–0 ms) and post-stimulus interval (70–3300 ms). Important to note here is the fact that the researcher did not know whether the stimulus in a given epoch belonged to "L" or "R" class, thus avoiding possible expectation/observation bias of *knowing* that the EMG trial and its (absent) motor response corresponds to a specific stimulus. Although visual inspection is a very demanding and lengthy process, which also depends on the researcher's expertise, yet it (still) provides more optimal results in terms of detection rate and accuracy than automatic, algorithm-based procedures, and thus it is used as final decision criteria (Hodges & Bui, 1996).

The number of epochs with detected motor responses was translated into a performance measure for each subject and each experimental condition as follows: We defined a correct response as a response where only right muscle movement was present for right class stimuli, and only left movements for left class stimuli. A “detection rate” is then defined as the ratio of the total number of correct responses to the total number of the presented stimuli. In case of “real” condition the detection rate should be 1 (or 100%) since each stimulus should be associated with detectable muscle activity. In practice it might be slightly smaller than 1 because the subjects might skip some responses to the stimuli either because of lacking attention or due to relaxation of their hand(s) when necessary to avoid an excessive amount of baseline EMG activation. In “imag” and “quasi” conditions the detection rate should be comparably small since none of these tasks implies overt movements. Nevertheless, one of the problems in defining this detection rate is the following. Completely noise-free EMG data is rarely achieved and some transient (< 10 ms) EMG activity might even occur at rest. Therefore, one important question concerns the specificity of EMG responses with respect to the corresponding stimulus. Considering right hand muscle activity, if motor responses are present with equal probability to “L” and “R” stimuli, then right hand EMG most likely does not reflect the subject’s intentional response but rather random activity or unspecified activity related to the experimental environment. However, in reality the number of left and right hand motor responses differs according to the stimulus class. At this point it is necessary to determine whether this difference is significant and thus reflects actual (correct) task performance, or whether the difference is not significant so that weak EMG activity does not represent specific motor responses to the stimulus. Therefore we tested this possibility by using binomial distribution to quantify the significance for the occurrence of left and right movements to “L” and “R” stimuli, respectively.

Comparison of pre- and post-stimulus interval in silent EMG trials

One of the main ideas of the present study is the performance of movements without overtly executing them in “quasi” condition. Thus the EMG amplitude in pre- and post-stimulus intervals should not differ in a considerable number of epochs. But even if we did not detect EMG responses by visual inspection, this would not be sufficient to preclude the possibility that some slight tonic muscle activity still might be associated with the subject’s efforts performing the task. Therefore, the analysis of root-mean square (RMS) values was performed for comparison of EMG amplitude in pre- and post-stimulus intervals (segmented

EMG data as described above). First we excluded epochs containing motor responses, as detected during visual data inspection. Then we used the non-parametric Wilcoxon's rank sum test (U-test; Bortz, 1999) to test for significant differences between pre- and post-stimulus values. The test was used since the number of epochs for pre- and post-stimulus intervals was not even. This is because some of the pre- and post-segments contained artifacts and were discarded from analysis, thus leading to unpaired values. Another reason for using this non-parametric test was that our EMG RMS values were not normally distributed. The comparison of EMG activity between pre- and post-segments was calculated individually for each subject and hand. It was also performed for "imag" condition, because another critical point of quasi-movements is that during their successful performance the motor output be undistinguishable from baseline EMG activity in "quasi" condition, and moreover not being different from (post-stimulus) baseline activity during motor *imagery*.

3.4 Relations between EEG and EMG activity

Given the fact that in some trials motor output is not completely reduced during the performance of quasi-movements, one of the most important questions in our study is whether peripheral feedback from (weak) muscle activity is strong enough itself to modulate ongoing neuronal oscillations. This is the crucial aspect for our aim of demonstrating that quasi-movements can substitute motor imagery in BCI context, given that this behavioral task provides a more effective modulation of neuronal activity, resulting in improved classification accuracy. Therefore, we employed four types of analysis in order to show that the classification of single EEG trials is not based on the occasional presence of EMG responses in "quasi" condition (and for comparison also in "imag").

Correlation between post-stimulus intervals in EEG and EMG

EEG data was filtered in time domain using opt_band, then spatial filtering was performed with common spatial pattern analysis (using four filters), which led to four CSP components with two for each movement class (as described above). In order to obtain amplitude values of EEG in post-interval, the Hilbert transform was applied to CSP components, and the mean amplitude was calculated for each epoch in the time interval of 70–3500 ms after stimulus (see also EMG preprocessing in the former section). Compared to EMG segments, 200 ms were deliberately added in post-stimulus interval in order to capture possible peripheral feedback after 3300 ms.

The two CSP components with strongest ERD for left and right class were selected for comparison with EMG in each condition ("quasi" and "imag"). Correlation coefficients were always obtained by using the non-parametric Spearman's rank correlation and tested for significance, compensating for rank ties and multiple comparisons (Nijsse, 1988; Bortz, 1999; Bortz & Döring, 2000).

Correlation of movement classes with EEG and EMG

Non-parametric rank-biserial correlation (Cureton, 1956) was calculated for correlation of EEG/EMG with the binary class variable of "L" and "R" stimuli, giving the strength of the relation of an epoch with a given class. This correlation provides information about how well the EEG/EMG values are associated with one of the two classes (-1 for left class, 1 for right class, as already mentioned for EEG single trial classification). Higher values correspond to a better discrimination of EEG/EMG between movement classes. Their values were calculated in the same way as described in the section above.

Significance of motor output for correct EEG classification

In cross-validation one usually obtains trials which are either correctly or incorrectly classified as belonging to left or right movement class. For each group of trials (classified vs. misclassified) the number of epochs with visually detected EMG responses was determined. Then the following ratios were calculated: M_{incorr}/NM_{incorr} and M_{corr}/NM_{corr}, where M_{incorr} and NM_{incorr} are the number of epochs with and without detected movements in *incorrectly* classified trials, respectively; M_{corr} and NM_{corr} are are the number of epochs with and without detected movements in *correctly* classified trials, respectively. These ratios were tested for significant differences by Fisher's exact test. The main idea behind this analysis was to show that the proportion of epochs with detectable motor responses us the same in correctly classified and misclassified trials. Thus, the output of the classifier is not primarily based on the presence of stimulus-specific EMG activity.

Correlation between classification errors of EEG and EMG

Another way for showing that the classification of oscillatory brain activity is not (or to minor extents) related to peripheral muscle activity is to demonstrate absence of significant correlation between the detection rate of EMG responses and the classification error derived from cross-validation procedure for EEG data. Both measures already have been introduced in the upper sections; for correlations Spearman's rho (described above) was calculated.

But the final and ultimate decision whether the amount of motor responses (especially for quasi-movements) is negligible for classifying EEG data in BCI applications, can be achieved by (Spearman's rank) correlation between classification errors for EMG and EEG. Therefore, the automatic classification of EMG epochs was performed on the basis of root-mean-square values of amplitude in post-stimulus interval (70–3300 ms). We used the same classification procedure as described above for EEG, but here our feature vectors were post-stimulus RMS values of muscle activity from left and right abductor pollicis brevis. Linear discriminant analysis and cross-validation procedure were applied to RMS values in order to obtain the classification error for “quasi” and “imag” conditions. In a first step, classification of single EEG and EMG trials was done for all available trials, that is, epochs without and with detected motor output. In the second step, classification was also run after the exclusion of epochs where EMG responses were visually detected. The main idea behind this additional classification was to show that the differences between errors for “imag” and “quasi” in EEG are not due to reafferent feedback from occasional weak muscle activity. Spearman’s rank correlation between classification errors (based on all or reduced number of trials) obtained for both conditions was computed. The assumption that classification of EEG is not due to peripheral activity can be demonstrated by showing that the improvement in terms of reduced classification error by quasi-movements, as compared to motor imagery, is not correlated to the classification improvement observable for EMG classification.

3.5 Statistical analysis across subjects

Spearman’s rank correlation as a non-parametric procedure was used for determining (significant) relations between subjective psychological and objective neurophysiological measures across subjects and conditions, compensating for rank ties. Bonferroni correction was applied when many pairs of correlations were used for quantification of the dependencies between parameters belonging to the similar comparison group (e.g. correlations between psychological measures). Bonferroni correction implies that original P-values should be changed to P/N, where N is the number of comparisons. For instance, if we have 15 subjects and 4 different correlations, then the P-value should reach a significance level of $P/60$ in order to be significant; all comparisons are independent. However, because in many cases our study is based on the demonstration of the *absence* of correlation, we have chosen a less strict version of Bonferroni correction. We only took into account the number of subjects N for the correction of P-values; this way we were reducing type II error.

Determining (significant) parameter differences was achieved by applying repeated measures ANOVA, with Bonferroni correction (unordered/flat) for multiple comparisons (Bortz, 1999; Bortz & Döring, 2000; Rosenthal & Rubin, 1984). All data analysis was performed by using Matlab (The MathWorks, Inc., version 6.5, 2002), ANOVAs were computed with SPSS (SPSS for Windows, version 12.0.1, 2003).

IV. RESULTS

4.1 Psychological testing

Questionnaires

When asked to indicate their general comprehension of the term “imagination”, the majority of subjects selected “mental rehearsal”, “seeing in the mind’s eye” or “fantasy” as related terms and “objective existence”, “facts” or “reality” as opposite terms. Motor imagery in general was circumscribed as purely mental processes without involvement of peripheral activity (no actual overt movement execution). For instance, motor imagery was described as movements which were “imagined in my mind” (S10), “not actually performed” (S11) or as “movement conduction only by my mind” (S4).

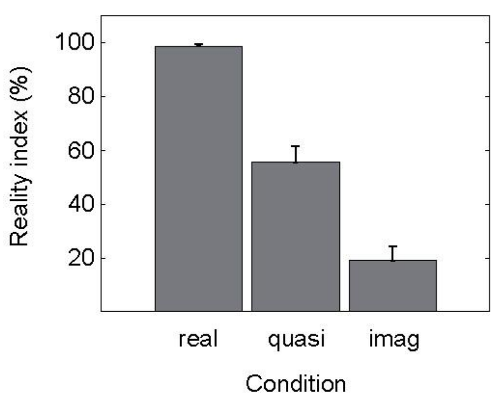
Imagery abilities as assessed by psychological questionnaires on average were indicated as being moderate to relatively high across subjects (*N*=17). The mean score for the Questionnaire Upon Mental Imagery (across all seven subscales, total number of 35 items) was 2.6 (*SD*=0.8), referring to “moderately clear and vivid” imagery as indicated by a rating of “3”. The mean score for the kinesthetic motor imagery subscale of the Vividness of Movement Imagery Questionnaire (20 items) was 2.2 (*SD*=0.6), indicating “clear and reasonably vivid” motor imagery by a rating of “2”. Important to note in this context is that these two questionnaires employ rating scales with a different number of steps (QMI: 7 steps, VMIQ: 5 steps), thus their ratings are not directly comparable. Please refer to Appendix D Table 1 for more detailed descriptive statistics.

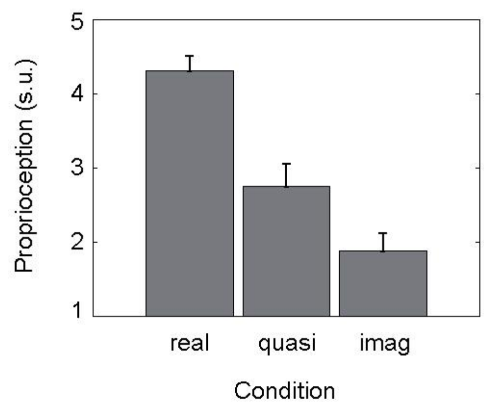
Subjective task experience

All subjects reported to be able to perform motor imagery of left or right thumb abduction after 1–2 minutes performing this task directly prior to session recordings, without receiving any further special training. Training for quasi-movements required ca. 10–20 minutes (together for both training by visual and verbal feedback) for reaching the stage where EMG activity to the presentation of the stimuli did not differ from pre-stimulus baseline activity. All subjects succeeded in this reduction of movement strength. This was also indicated by subjective rating on a discrete scale ranging from “minimum” to “maximum” strength (see *Methods* section above). All subjects (*N*=17) marked very close to or completely at the “minimum” pole. One subject had to be excluded from subsequent analysis of psychological data obtained for quasi-movements (and in case of its relation to objective measures, see below) because of not being able to perform “quasi” task properly. This was not due to lack of the ability to reduce movement strength but rather to the subject’s understanding of the "quasi" task requirements, reporting having switched to motor imagery during "quasi" sessions without trying to perform quasi-movements anymore.

The subjective experience of "imag", "quasi" and "real" conditions was assessed in two standardized task ratings (cf. Appendix B). Firstly, when rating whether the task performance belonged rather to "real" or "imagery" category (continuous scale: "reality index", cf. *Methods*) and secondly, evaluating the proprioceptive sensation of muscle contractions.

ANOVA showed a significant effect of the task condition for "reality index" ($F_{2,30}$=116.8, P<0.001), and post-hoc tests demonstrated that the mean value was highest in "real" condition and weakest in "imag" condition. An intermediate value was obtained for the subjective evaluation of quasi-movements (Figure 1); see also Appendix D Table 1. All pair-wise comparisons between "reality indices" were significant (P<0.001). A significant condition effect was also the case for "proprioception" ($F_{2,30}$=33.5, P<0.001) with the same relationship as for the "reality index" (Figure 2), all pair-wise comparisons of the mentioned variables were significant (P<0.05).





Left: *Figure 1.* Reality index in three experimental conditions.
Right: *Figure 2.* Evaluation of proprioceptive sensation in three experimental conditions.
Real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, s.u. – scale units, error bars – standard error of the mean.
Calculation of the "reality index" (continuous scale): reality index=(scale length-rating value)/scale length*100 measured in cm; value of respective task rating measured from left side of the scale;
100% indicate that the task is evaluated as completely "real", 0% as completely "imagined".
Evaluation of "proprioception" (discrete scale, 5 steps): 1=none, 5=strongest.

Subjects consistently confirmed trying or *intending* to execute "real" movements in "quasi" task when asked after session recording. But surprisingly, 15 out of 16 subjects remarked *spontaneously* during training or after recording that quasi-movements "feel like imagery". Furthermore, when asked to categorically rank all three tasks, the order was consistently "imag", "quasi", "real" with respect to their subjective similarity to "reality" for 14 subjects, whereby in two cases the order was even "quasi", "imag", "real".

12 subjects (not all assessed) ranked the tasks in the order "quasi", "imag", "real" with respect to the subjectively required amount of concentration and effort for accomplishing the task.

In one case, motor imagery was evaluated as being more demanding than the performance of quasi-movements.

Relations between task ratings

Reality indices from "imag" and "quasi" conditions were highly and significantly correlated (Spearman's rank correlation, ρ=0.71, P<0.002, Figure 3), but not to "real" condition. RIs were not significantly correlated within conditions. Evaluations of proprioceptive sensations were not significantly correlated within and across conditions.

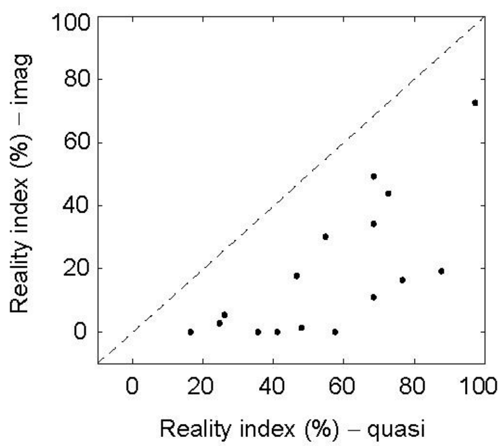


Figure 3. Correlations between reality indices for quasi-movements and kinesthetic motor imagery.
Imag – kinesthetic motor imagery, quasi – quasi-movements, dashed line – main diagonal.
Spearman's rank correlation, ρ=0.71, P<0.002.
Calculation of the "reality index" (continuous scale): reality index=(scale length-rating value)/scale length*100 measured in cm; value of respective task rating measured from left side of the scale;
100% indicate that the task is evaluated as completely "real", 0% as completely "imagined".

Additional observations during experimental recordings

All subjects also addressed the paradoxical nature of quasi-movements, namely the conflicting dual-task situation of "doing" movements and not doing them at the same time. Training lasted up to 30 minutes for one subject until movement strength was reduced appropriately. Interestingly, when switching from visual EMG feedback to verbal feedback, this had a pronounced effect on the majority of subjects: still present motor responses (although already very weak) immediately disappeared after the first few trials.

4.2 EMG

Subject's compliance for performance of quasi-movements

Exemplary trials of EMG activity for single subjects in all three conditions are shown in the Appendix E Figures A2, A3, and A4. Subject's compliance in "quasi" condition could be inferred from the fact that from time to time motor responses could be seen in EMG traces, which clearly exceeded pre-stimulus baseline level. In this case the researcher instructed the subject in between trials to reduce movement strength again. Figures A2 (b: trials 65, 69) and A3 (a, c) give an example of motor responses during the execution of quasi-movements.

They are very short-lasting (<10 ms) and of extremely small amplitude, though clearly distinguishable in six movements in pre-stimulus interval, as required by the task. Furthermore, very small (pre-stimulus) baseline amplitude (of ~ 4 µV) is optimal for detection of these weak EMG responses. Important here is to note that this beautiful response pattern of exactly six movements within such small amplitude range was absolutely rare (like shown in Figure A3) and were only found in two trials of two subjects. An interesting observation is the comparison of trials 90 and 124 in S7: pronounced muscle activity of very low amplitude can be seen during the performance of quasi-movements – *but a similar pattern is also present during motor imagery*.

On average, approximately 2 motor responses ("bursts" in EMG) were visually detected in "quasi" condition, with a mean amplitude of 32 µV. Values are given here always averaged for both hands; mean values for "imag" condition were comparable (27 µV).

Although movement strength was required to be relatively weak (but resulting in visible thumb movements), EMG bursts (on average 6–7 movements) lasted for tens of milliseconds with a mean amplitude being as high as ~340 µV (see Appendix D Table 2 for detailed statistics). Therefore it is so amazing to see the very short-lasting motor responses of quasi-movements on average ranging from 8 (!) to 46 µV. Figure A4 shows root-mean-square values of EMG amplitudes averaged across trials for all three conditions from left and right abductor pollicis brevis (subject S11). Trials containing visually detectable motor output were excluded from "quasi" and "imag" condition; as expected, post-stimulus baseline RMS are not distinguishable.

One subject was excluded completely from EMG analysis because of having excessive amount of background muscle activity in all three conditions. Another subject was excluded because of inappropriate task performance in "quasi" condition (see above), resulting in a sample size of N=15 for EMG analysis.

Comparison of pre- and post-stimulus interval in silent EMG trials

After exclusion of epochs containing motor responses, the root-mean-square values of pre- and post-stimulus EMG were about 2 µV in “imag” and “quasi” conditions (Figure 4).

Left hand had slightly larger EMG amplitudes for both pre- and post-stimulus intervals, compared to right hand EMG due to the occasional presence of residual electrical signals from heart activity. Slightly higher values of EMG amplitude in “quasi” condition for pre- and post-stimulus intervals are likely to be associated with the fact that this task was most demanding and therefore contained slightly higher background muscle activity (cf. Appendix D Table 2).

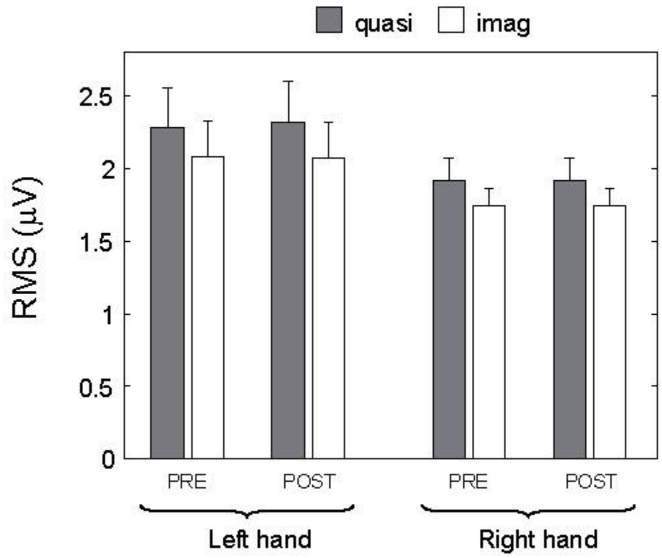


Figure 4. EMG in pre- and post-stimulus intervals for quasi-movements and kinesthetic motor imagery. PRE – pre-stimulus interval, POST – post-stimulus interval, RMS – root mean square, quasi – quasi-movements, imag – kinesthetic motor imagery, error bars – standard error of the mean; pre-stimulus interval: -1000–0 ms, post-stimulus interval: 70–3300 ms.

Still, repeated measures ANOVA across subjects separately for each hand showed no significant condition effect (“quasi”, “imag”), time interval (“pre”, “post”) or interaction of condition vs. interval (P>0.05 for all comparisons). Therefore, both conditions had similar muscle activity during task performance. Furthermore, within subject comparisons of pre- and post-stimulus EMG amplitudes by Wilcoxon’s rank sum test (U-test) demonstrated no significant difference (P>0.05), when each subject and hand were analyzed separately in “imag” and “quasi” condition. “Real” condition was not included in any comparisons for the obvious reason of always containing strong post-stimulus EMG activity.

Detection of (weak) motor responses

In general, it seems to be that our recording conditions were more stringent compared to what is usually used as standard criteria for the (visual) detection of motor responses in the abductor pollicis brevis, e.g., in transcranial magnetic stimulation (TMS) research. In those studies the threshold values for considering muscle activation are often placed as high as 50 µV. Ideally, epochs in "imag" and "quasi" conditions should not contain EMG activity as specific reaction to a stimulus, yet both tasks showed some epochs with detectable motor output (though very small); compare with Figures A2 and A3 (Appendix E). We were interested in the significance of and the difference between the amount of trials with detected motor output in the three conditions. First, we applied binomial distribution testing (cf. *Methods*) for "imag" and "quasi" conditions in order to check whether occasional motor responses indeed corresponded to specific task performance with respect to stimulus presentation or rather reflected unspecific muscle activity (e.g., arousal-related). Eight subjects had a significant ($P<0.05$) association of EMG responses with the respective stimulus ("L" or "R") in "quasi" condition – and four subjects also in "imag" condition. This testing also indicates the significance of the calculated detection rates (compare *Methods* section) for each subject, as shown across subjects in Figure 5 for each condition (cf. Appendix D Table 2 for statistics).

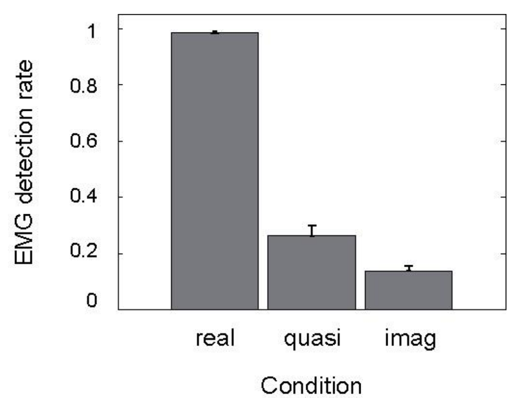


Figure 5. Detection rate for EMG in post-stimulus interval for three experimental conditions.
Real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, error bars – standard error of the mean; post-stimulus interval: 70–3300 ms.
Calculation of the EMG detection rate: detection rate=(RH+LH)/(trials_R+trials_L)
RH, LH: only right or left hand responses to stimulus "R" or "L", respectively; no simultaneous responses; trials_R, trials_L: all trials for right or left hand=(108-epochs with artifacts); this ratio of the total number of detected correct motor responses to the total number of the presented stimuli should be close to zero for motor imagery, and 1 for actual movement execution. The obtained slightly smaller value for "real" can be the case because subjects might skip a few responses due to lacking attention or relaxation of their hand(s) in order to avoid excessive amount of baseline muscle activation.

Repeated measures ANOVA demonstrated a significant effect of the task condition on the detection rate ($F_{2,28}$=522.9, P<0.001). As expected, the detection rate for was almost at maximum for movement execution and it was smallest for motor imagery-task. The detection rate for "quasi" task was slightly larger than that during "imag", also confirmed statistically by post-hoc testing (P<0.05). But even though subjects had non-zero detection rates in "imag" and "quasi" conditions, the majority of detectable motor responses were not related to the subject's performance of the task, which required a strict correspondence between stimulus presentation and motor output (left hand movements to "L", right hand movements to "R", no simultaneous hand movements; cf. Table 2).

4.3 EEG

One subject had to be excluded completely from EEG analysis because of not showing any rhythmical activity (thus no modulation in any condition), another subject was excluded due to inappropriate performance of the "quasi" task (see above), and a third because of insufficient amount of recorded data. Accordingly, sample size was reduced from 17 to 14 subjects for EEG analysis.

Modulation of ongoing oscillatory activity in the alpha range

As expected, spontaneous alpha oscillations in 8–13 Hz frequency range were decreased in amplitude during performance in all three conditions. Figure A5 in Appendix E shows topographic plots of alpha attenuation in a representative subject (S11; compare also EMG data in Figures A2 and A4). The strongest attenuation occurs in those channels above central sensorimotor areas. ERD is most pronounced in the contralateral hemisphere. Repeated measures ANOVA with the two factors "condition" (in three levels) and "hemisphere" (two levels) was calculated separately for each movement class. It demonstrated a significant condition effect for left hand movements ($F_{2,26}$=21.7, P<0.001) and right hand movements ($F_{2,26}$=16.5, P<0.001). Post-hoc analysis revealed that ERD in "real" condition was significantly stronger than in "quasi" and "imag" (P<0.05). ERD was not significantly different between the latter two tasks. Figure 6 shows ERD strength for all conditions and both hemispheres. See Appendix D Table 3 for statistics.

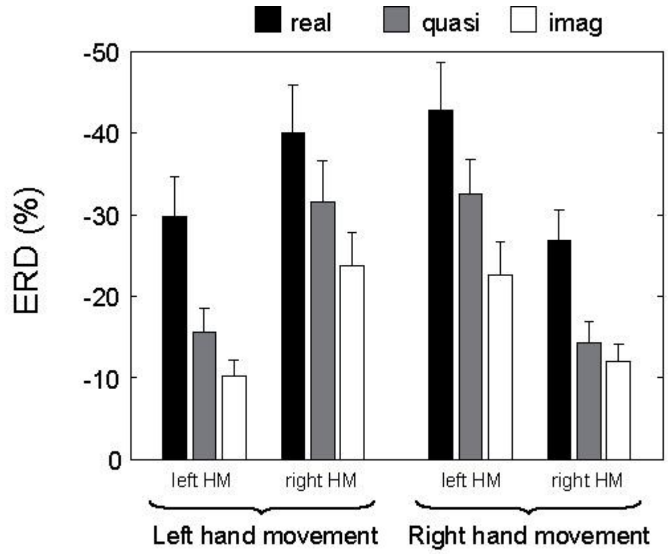


Figure 6. ERD in three experimental conditions.
ERD – event-related desynchronization, HM – hemisphere, real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, error bars – standard error of the mean.
Calculation of ERD: ERD=(POST-PRE)/POST*100
POST=averaged electrophysiological activity in post-stimulus interval over channel with strongest ERD (70–3330 ms), PRE=averaged electrophysiological activity in pre-stimulus interval over channel with strongest ERD (-500–0 ms); negative values indicate the attenuation of spontaneous oscillations in the frequency range of 8–13 Hz in the most reactive channels over central sensorimotor regions, positive values indicate an enhancement of these rhythms.

Similarity between spatial activation patterns

CSPs demonstrated clear topographic differences between the two classes with largest ERD in opt_band range over contralateral hemispheres, as can be seen exemplarily in Figure A6–A8 (Appendix E). However, CSPs appeared quite similar by visual inspection across the task conditions. In order to measure the differences in spatial topography of EEG across conditions we calculated a measure quantifying the similarity between CSP maps (see *Methods*). Repeated measures ANOVA (calculated separately for left and right movement class) confirmed this impression by not showing significant dissimilarities between any of the three conditions (P>0.05 for all comparisons).

Single trial EEG classification

The selection of optimal frequency bands, time intervals, and CSP filters for discrimination between left and right stimulus class was performed automatically as described above (cf. *Methods*). Only in three data sets (two for “imag”, one for “real) we used additional manual adjustments for opt_band and opt_ival because the automatic procedure resulted in inadequate selection of limits. Figure A9 (Appendix E) shows automatically defined frequency bands, time intervals, and CSPs for all three tasks in a representative subject (S11; compare also

EMG and ERD data). Grand-average limits for opt_band were 9.4–13.9 Hz for “real” condition, 9.1–13.8 Hz for “quasi”, and 8.6–13.4 Hz for “imag”, respectively. These values indicate that neuronal oscillations in the alpha frequency range are most sensitive to the discrimination between left and right movement classes. Grand-average limits for opt_ival were 907–3180 ms for “real”, 669–2936 ms for “quasi”, and 562–2572 ms for ”imag”. The amount of epochs used for classification (average of left and right classes combined) was N=103 in all conditions, containing *all* trials without or with detected motor output in EMG. Mean classification error differed across conditions with 0.08 for “real” condition, 0.12 for “quasi”, and 0.23 for “imag”. An error of 0.50 indicates random classification in one or the other movement class (50% of the data set is classified as belonging to left class, 50% to right class); cf. *Methods*. Accordingly, the respective classification accuracy is then obtained by subtracting 1-error (multiplied by 100 for percentages). For example, the mean error of 0.12 for “quasi” indicates a classification accuracy of 88% correctly classified trials (in this case 91 correct trials out of 103; the remaining 12 were erroneously classified like right hand movements as left hand movements or *vice versa*). Our obtained classification error of 23% for motor imagery is comparable to those reported in literature (cf. for instance Dornhege, Blankertz, Krauledat, Losch, Curio & Müller, 2006). Detailed descriptive statistics can be found in Appendix Table 4. The mean classification error for all conditions is presented in Figure 7.

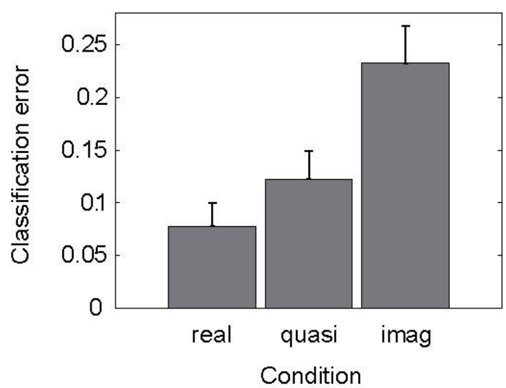


Figure 7. Classification error in EEG for three experimental conditions.
Real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, error bars – standard error of the mean.
Calculation of the classification error: ERROR=(misclassified trials/all classified trials)
0=correct classification of all trials, 0.5=random classification (on chance level).

Differences between the conditions were significant as calculated by repeated measures ANOVA ($F_{2,26}$=22.4, P<0.001) along with significant post-hoc pair-wise testing (P<0.05 for all comparisons). These results indicate that quasi-movements in general provide an effective means to modulate ongoing neuronal oscillations, more effective than motor imagery.

The classification accuracy for quasi-movements is much closer to the one obtained for movement execution. This expected but nevertheless pleasing result also holds especially for subjects with *low* “imag” classification accuracy compared to *high* classification accuracy in “real” condition, as confirmed by non-parametric Spearman correlation (ρ=0.78, P<0.001) and shown in Figure 8.

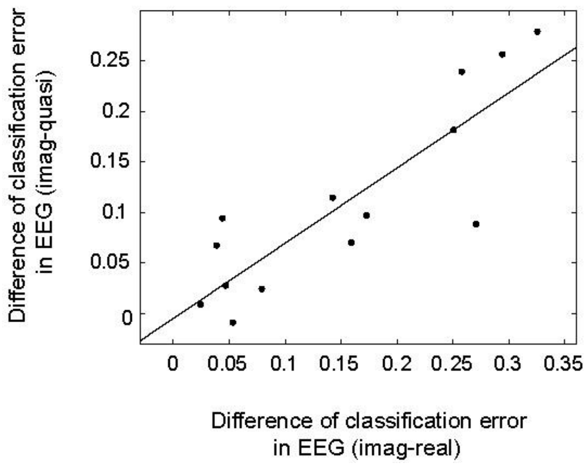


Figure 8. Correlation between differences of EEG classification errors.
Real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, line – least squares trend, Spearman’s rank correlation, ρ=0.78, P<0.001.
Calculation of the classification error: ERROR=(misclassified trials/all classified trials)
0=correct classification of all trials, 0.5=random classification (on chance level).

The difference between errors in “imag” and “real” have been correlated to the difference between “imag” and “quasi”, calculated individually for each subject. Important to emphasize here is that the absolute difference between classification errors of “imag” and “quasi” of 11% (as in Figure 8) results in a *relative improvement*, calculated individually for each subject, of 54% with a range of 18–86% (N=9). This relative improvement reflects drop of classification error from 30% for “imag” to 15% for “quasi” (with 8% for “real); cf. Table 5 Appendix D. Note that in these calculations five subjects had been excluded for the following reason: As can be seen already in Figure 8, some subjects show only slight changes in classification accuracy at all (across the three conditions). In those cases, for instance a relative improvement of 100% from “imag” to “quasi” can refer to an absolute reduction of classification error from 7 to 3%, respectively (like in subject S12), with zero error for “real”. Although by the figures this result is correct, capturing a relative improvement by quasi-movements is only meaningful in those subjects who are at least *able* to modulate brain activity to a certain extent, as reflected in considerable differences between errors for “imag” and “real”. Like for a subject (S13) with an initially high classification error for motor imagery of 0.41, which is close to random classification, a relative improvement of 63% reflects a drop to considerable 0.15 for “quasi”, with 0.11 for “real” movements. In terms of classification accuracy: initially low 59% for “imag” were enhanced by quasi-movements to 85% correctly classified data (compared to only slightly better 89% for “real”). Compare Table 5a, 5b, and 5d (all in Appendix D) for information about other subjects.

Therefore, in order to capture “meaningful” relative improvement by quasi-movements compared to imagined movements, the mean absolute distance between classification errors for all condition-combinations was calculated for each subject (N=14). The differences were sorted in ascending order as shown in Figure 9 (and Table 5c).

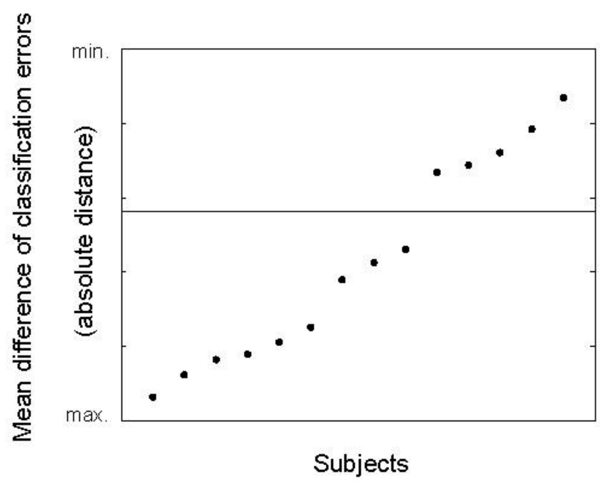


Figure 9. Mean difference of classification errors across all three experimental conditions.
Min. – minimum absolute distance, max. – maximum absolute distance, line – cut-off at the largest discontinuous gap.
Calculation of the classification error: ERROR=(misclassified trials/all classified trials)
0=correct classification of all trials, 0.5=random classification (on chance level).
Calculation of the absolute difference between classification errors:
DIFF=(abs(real-quasi)+abs(real-imag)+abs(imag-quasi))/3, abs – absolute values.

This measure can range from 0 to 0.50 for zero and largest error differences, respectively; in the present data set it ranges from 0.02 to 0.22 (subjects with minimum and maximum differences). A clear discontinuity can be seen among the sorted values. Subjects lying above this discontinuity were excluded (N=5) and the mean difference between “imag” and “quasi” classification error was calculated for the remaining subjects, resulting in the values reported above (cf. also Table 5d).

4.4 Relations between neurophysiological and psychological measures

Correlations between EMG and psychological parameters

As can be seen in Figure 10, no significant correlation (Spearman's rank correlation for all tested relations) was found between proprioceptive sensation of muscle activity, as evaluated by subjective task ratings, and the amount of trials with visually detected motor responses (detection rate; cf. *Methods*) within "imag" and "quasi" condition (for "quasi": ρ=0.14, P=0.63, for "imag": ρ=0.18, P=0.52). Significance was also absent when correlating the perceived degree of "reality" ("reality index") of these conditions with the detection rate of EMG.

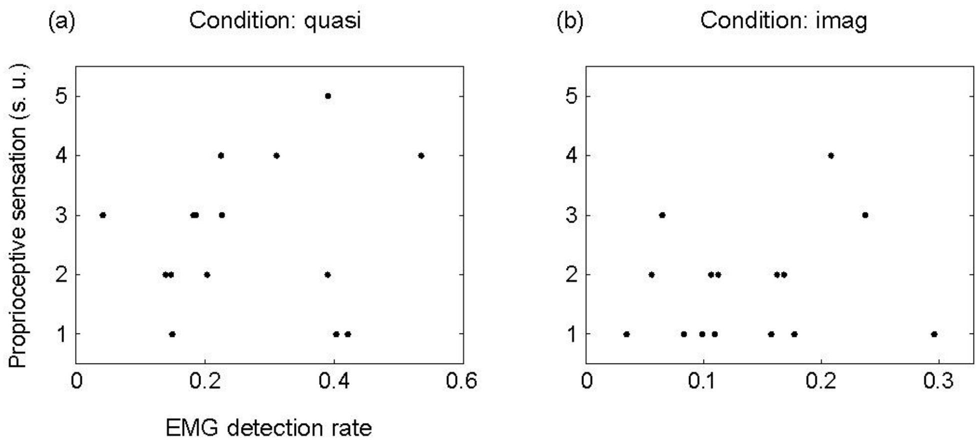


Figure 10. Insignificant correlations between subjective evaluation of proprioceptive sensation and EMG detection rate for quasi-movements and kinesthetic motor imagery.
Quasi – quasi-movements, imag – kinesthetic motor imagery, s. u. – scale units.
Spearman's rank correlation for "quasi": ρ=0.14, P=0.63, for "imag": ρ=0.18, P=0.52.
Evaluation of "proprioception" (discrete scale, 5 steps): 1=none, 5=strongest.
Calculation of the EMG detection rate: detection rate=(RH+LH)/(trials_R+trials_L)
RH, LH: only right or left hand responses to stimulus "R" or "L", respectively; no simultaneous responses
trials_R, trials_L: all trials for right or left hand=(108-epochs with artifacts); this ratio of the total number of detected correct motor responses to the total number of the presented stimuli should be close to zero for motor imagery, and 1 for actual movement execution.

Correlations between EEG and psychological parameters

Correlations (Spearman's rank correlation for all tested relations) between subjective task ratings ("reality index", "proprioception") and the amount of Laplacian ERDs were insignificant within all task conditions. This was also the case for the correlation with classification errors obtained by single trial EEG classification. Significant correlation was also absent when relating the "similarity indices" between spatial electrophysiological activity patterns (CSPs, see *Methods*) of different conditions with the similarity of "reality indices". The "similarity index" for a task's degree of "reality" was calculated as the absolute difference between corresponding "reality indices" of two conditions as (quasi-imag), (quasi-real), and (imag-real). It varies from 0 to 100, with 0 corresponding to complete similarity between task ratings, and 100 to completely dissimilar "reality indices", where one task is marked as totally "real" and the other as "imagery". Absence of significant correlation indicates that although performance of imagined, executed, and quasi-movements does not correspond to significantly different topographic neuronal activation (see *Results* for EEG above), the subjective task experience is very distinct (as already shown in Figure 2). When correlating Laplacian ERDs as well as classification errors with general imagery abilities as assessed by standardized psychological questionnaires (QMI and VMIQ, see *Methods*) for all task conditions, correlations were never significant.

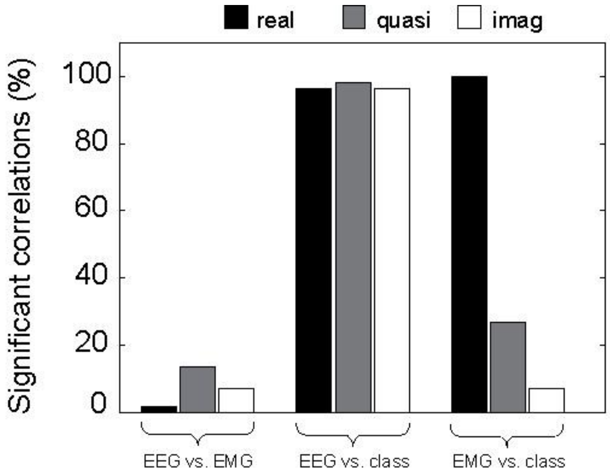
4.5 Relations between EMG and EEG activity

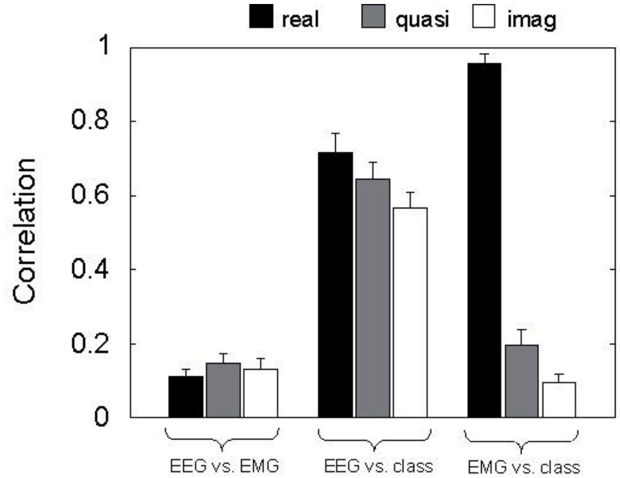
The performance of quasi-movements as well as kinesthetic motor imagery of thumb abduction occasionally involves slight muscle activity, as our results demonstrate. Therefore, an important question was to investigate whether this motor output might be related to brain activity, so that residual EMG attenuates spontaneous oscillations stronger in trials with detectable motor responses than in trials without such responses. As described above, four different approaches were used to show that EMG activity does not significantly contribute to the reactivity of EEG, especially for "quasi" condition.

Correlations between activity in EEG and EMG in post-stimulus interval

Spearman's rank correlation between the root-mean-square values of EMG amplitude and the mean amplitude of components from common spatial pattern analysis in post-stimulus interval demonstrated, that only in a small number of data sets significant correlations had been obtained for the three conditions. These were in all cases of very weak strength. On average were 2% of the correlations in "real" condition significant, 13% in quasi", and 7% in "imag" (P<0.05 for all coefficients with Bonferroni correction, cf. *Methods*).

Figure 11 shows percentages of significant correlations, Figure 12 shows grand-average values of all coefficients, regardless of their significance. Compare with Appendix D Table 6 for descriptive statistics. Furthermore, the amount of contra-lateral ERD (as derived from CSP analysis) is not significantly related to the amount of trials with detectable motor output, as determined by calculation of EMG detection rate (see *Methods*).





Left: *Figure 11*. Percentages of significant correlations for EEG and EMG in three experimental conditions.
Right: *Figure 12*. Absolute values of correlations for EEG and EMG in three experimental conditions.
Real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, EEG vs. EMG – percentages of significant Spearman's rank correlations between root-mean-square values of EMG amplitude and mean amplitude of CSP components in post-stimulus interval, EEG vs. class – percentages of significant biserial rank-correlations and stimulus class (left vs. right), error bars – standard error of the mean.

Correlation of movement classes with EEG and EMG

Rank-biserial correlation was calculated separately for EMG amplitude and ERD in post-stimulus intervals, using class-label information as second variable. As mentioned above, this correlation allows determining to what extent EEG or EMG activity can be used as the predictor of a class information (left vs. right).

For EEG, a large number of data sets (96 to 98%) had significant and high correlations in all three conditions. But for EMG only in "real" condition 100% of correlations in the data set were highly significant and near to 1. Whereby only 27% of "quasi" and 7% of "imag" data set showed significant correlations, which were of negligible strength (P<0.05 for all coefficients with Bonferroni correction); cf. Figures 11 and 12 above.

Significance of motor output for EEG classification

Fisher's exact test demonstrated that the proportion of epochs with detected movements was not significantly different in correctly and incorrectly classified epochs for all subjects within all conditions (P>0.05 for all comparisons).

Correlation between classification errors of EEG and EMG

There was no significant correlation (Spearman's rank) between EMG detection rate and the classification error by single trial EEG classification for "quasi" and "imag" condition (for "quasi": ρ= -0.11, P=0.72, for "imag": ρ=0.25, P=0.40), as shown in Figure 13.

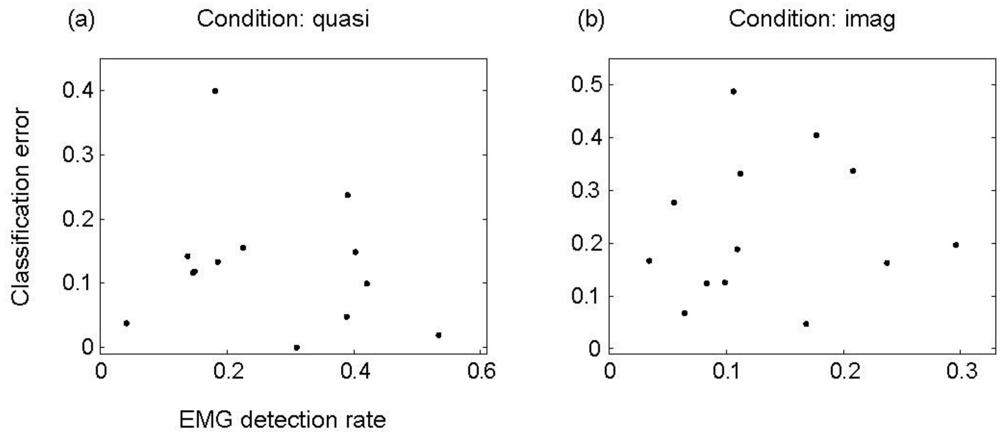
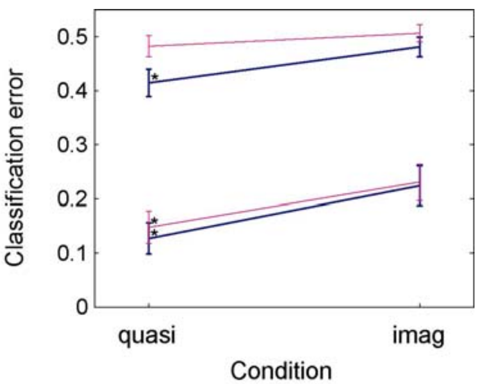


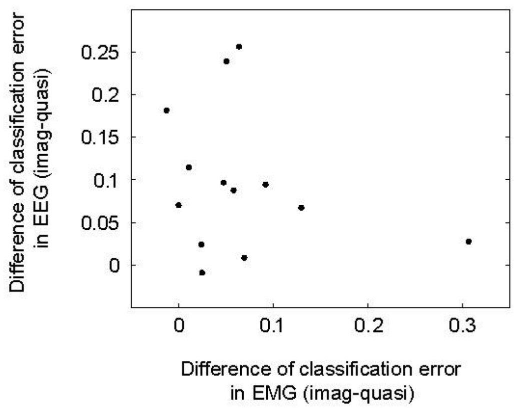
Figure 13. Insignificant correlation between EMG detection rate and EEG classification error in quasi-movements and kinesthetic motor imagery.
Quasi – quasi-movements, imag – kinesthetic motor imagery.
Spearman's rank correlation for "quasi": ρ= -0.11, P=0.72, for "imag": ρ=0.25, P=0.40.
Calculation of the classification error: ERROR=(misclassified trials/all classified trials)
0=correct classification of all trials, 0.5=random classification (on chance level).

Automatic classification in EMG for all available epochs demonstrated that the classification error for "quasi" condition (0.41) was significantly smaller than for "imag" condition (0.48), as determined by Wilcoxon sign rank test (P<0.002). We then excluded epochs with detected EMG responses and run classification procedure again. After this exclusion the classification errors increased in both sessions (0.48 for "quasi", 0.51 for "imag") and were not statistically distinguishable anymore (P<0.45), as depicted in Figure 14 below. Also the classification errors for EEG single trial analysis are shown in this figure. The much higher classification accuracy for EEG data in general, as already reported above, with significant differences between "quasi" and "imag" classification errors (cf. Figure 7), is still present even after exclusion of epochs containing EMG responses. "Quasi" condition still had significantly smaller classification error (0.15) compared to "imag" (0.23), as revealed by Wilcoxon sign rank test (P<0.01).

The number of epochs used for the classification with exclusion of motor responses (N=78 for "quasi" and N=92 for "imag") was smaller than initially obtained (N=104 for "quasi" and "imag"). Amazing here is that although in some subjects the number of epochs had to be reduced up to approximately 50–60% because of EMG contamination, the classification accuracy for EEG data is only marginally affected in these cases (like S6 or S7; compare Table 5b in Appendix D for exact values). Thus Figure 14 provides the demonstration of the proposed assumption that single trial EEG classification is not related to occasional muscle activity or reafferent feedback from the periphery. This result is further strengthened by absent significant correlation between classification error differences ("imag"-"quasi") for

EMG and EEG (ρ= -0.2, P=0.52), indicating that an improvement of classification accuracy by quasi-movements in EEG is not related to the amount of improvement obtained by EMG classification (Figure 15 and Table 7).





Left: *Figure 14*. Classification errors for EEG and EMG data in quasi-movements and kinesthetic motor imagery.

Top: classification errors for EMG, bottom: classification errors for EEG; blue lines – classification procedure on all trials of the data set, purple lines – classification procedure only on trials *without* detected motor responses; asterisk – significant difference between classification error for quasi-movement and kinesthetic motor-imagery condition (Wilcoxon sign rank test, P<0.01); quasi – quasi-movements, imag – kinesthetic motor imagery. *Calculation of the classification error:* ERROR=(misclassified trials/all classified trials) 0=correct classification of all trials, 0.5=random classification (on chance level).

Right: *Figure 15*. Insignificant correlation between differences of classification errors for quasi-movements and kinesthetic motor imagery in EEG and EMG.

Spearman's rank correlation: ρ= -0.2, P=0.52.

V. DISCUSSION

5.1 Can you do a movement without doing it?

As we initially asked ourselves this question, it seemed to be a paradoxical task, impossible to solve. The performance of a movement without its overt execution, as detectable by objective measures like EMG, should be an unsolvable challenge because both tasks are mutually exclusive and cannot be performed simultaneously. Yet our study provides neurophysiological and psychological evidence for a clear “yes” to this question.

How can that be? The paradox is indeed not solvable from only one of the two perspectives separately; neither from an external, objective viewpoint (the researcher observing and analyzing data) nor from the subjective viewpoint of the performer. But when addressing both perspectives by neuroscience and (neurocognitive) psychology and combining results from both methods, resolving the paradox becomes possible. All subjects reported that they intended and executed genuine movements – from their viewpoint movements indeed had been performed. Yet in the majority these “movements” could not be detected by the objective measurement.

Avoiding philosophical aspects of the introduced paradoxical question and staying on neurophysiological grounds, it would be sufficient to say that our results indicate the possibility to perform movements with practically zero-force, a so-called quasi-movement. Evidence and implications will be discussed below, as well as the relevance of quasi-movements on neuropsychological, neurophysiological, and (neuro-) computational grounds with special emphasis on BCI application.

5.2 Quasi-movements and motor control

“The motor system receives thousands of sensory inputs and ultimately controls thousands of motor units, which gives it a very high-dimensional control problem to solve. For example, consider the 600 or so muscles in the human body as being, for extreme simplicity, either contracted or relaxed. This leads to 2^{600} possible motor activation patterns, more than the number of atoms in the known universe” (Wolpert, Ghahramani, & Flanagan, 2001, p. 491).

In the present study the activity of only one small muscle (abductor pollicis brevis) in the left and right thumb is studied during motor imagery, actual thumb abduction, and the performance of quasi-movements. In contrast to a vast majority of motor-imagery studies addressing rather complex movements and which involve a larger number of muscles, the abductor pollicis brevis is an ideal candidate for the detection of smallest activations: the thin muscle is superficially located, and the contracting fibers are close to the surface electrode.

Root-mean-square values of EMG activity at rest were ~ 2 μV for "quasi" and "imag", and ~ 4 μV for "real", which are smaller or equal to previously reported values (Stinear et al., 2006; Zoghi & Nordstrom, 2006).

"From a computation viewpoint the brain is a processing system that converts inputs into outputs. The outputs are the motor commands acting on ensembles of muscles and the inputs are the aggregate of sensory feedback provided by our sense organs and derived internally from an efference copy of the descending motor command. Motor control can be thought of as the process of transforming sensory inputs into consequent motor outputs" (Wolpert et al., 2001, p. 488). Sensorimotor control can be studied on different levels with respect to e. g. behavioral, neuronal or computational aspects. Modeling and simulation of (human) movements use the concept of "internal models" which can be described as "neural mechanisms that can mimic the input/output characteristics, or their inverses, of the motor system. Forward internal models can predict sensory consequences from efference copies of issued motor commands. Inverse internal models… can calculate necessary feedforward motor commands from desired trajectory information" (Kawato, 1999, p. 718), whereby both model types can work in combination by paired modular organization (Haggard, 2005; Haruno, Wolpert, & Kawato, 2001; Miall, 2002). Research aims at the explanation and prediction of sensorimotor function, explanation of motor learning, adaptation, the role of sensory feedback and contextual information, the interplay of perception and action, as well as finally identifying responsible neural networks and determining their (interactive) processing. One of the difficulties in defining an optimal control model for a movement in order to reach an optimal performance level is the specification of the cost function which should be minimized. This quantitative definition of task goal and performance, respectively, can be clearly defined in the case of quasi-movements: complete minimization of produced force. But with this objective, quasi-movements cannot be studied with the array of tools which rely on movement parameters like force, acceleration, velocity, joint angles and torques, trajectories or limb position, since there is no measurable movement to study. Still, the paradigm of quasi-movements should be congruent with and can be embedded in traditional and current (computational) models of motor control (please refer e.g. to Bullock & Grossberg, 1998; Haruno et al., 2001, Kawato, 1999; Roy, Hsiao, & Mavridis, 2004; Todorov, 2004, Wolpert et al., 2001). This should be especially relevant for determining *how* the performance of quasi-movements is *learnt* by the subject in order to achieve the goal-state of zero motor output: through gradual decrease of the produced muscle force. Staying in the framework of (neuroscientific) computational theory, for example an inverse model of quasi-movements would be related to the planning of a movement (here with respect to the musculi abductor pollicis brevis) with minimized or zero force and the estimation/selection of the appropriate motor command, along with the production of an efference copy of the command (Miall, 2002; von Holst, 1954; "corollary discharge", Sperry, 1950). The efference copy is fed to a feedforward model of the movement, which would predict practically "zero" sensory feedback. If the prediction is confirmed by absent reafferent feedback, then this linked inverse and forward model of the movement is appropriate and responsible for the correct task performance. If there is a mismatch between expected and delayed incoming sensory feedback, the internal models are modified (feedback error-learning).

However, if the performance of quasi-movements requires explicitly zero force and no actual trajectory, which movement parameters still can be coded? What is actually "felt" during quasi-movements? What could be the role of an efference copy in absence of reafferent feedback from the periphery with respect to the "conscious" sense of the movement? Why are quasi-movements subjectively perceived as more "demanding" in terms of required effort and concentration? In what way quasi-movements could stand in relation to motor imagery?
And how is the performance of quasi-movements reflected in brain activity? All these questions may provide an avenue to an understanding of the demonstrated improvement of classification accuracy in BCI context and will be surveyed in the following sections.

5.3 Performance and subjective experience of quasi-movements

Indeed, the most straightforward way to comprehend the nature of quasi-movements could be to look at how the optimal state of their "performance" (with absent overt execution) is reached. In the first place, two exclusive desired task-goals are present, which are translated into (motor) commands: execution and inhibition of a movement with initial weak strength. When subjects were presented with their own EMG activity in the training condition, they started with the movement strength from "real" task (compare *Methods* for instructions and *Results* for EMG amplitudes). Then they gradually decreased motor output by sensory feedback, like proprioception or visual or verbal feedback, until the desired state of zero movement strength is reached. It might be the case that during this procedure these two gradually increasing competing commands are combined into a third type, namely to perform quasi-movements right away; here with the side-notion that "the whole is different than the sum of its parts".

This performance can only be achieved by motor learning, as reflected in training times of approximately 15 up to 30 minutes. The “motor” (?) command to perform quasi-movements can be conceived as a sensitive balance between excitatory and inhibitory processes, in its ideal state comparable to phase cancellation in the frequency domain. This equilibrium state might be pictured as a ball upon a potential “hill”. Supra-threshold perturbations push the ball rolling into one of the two “wells”: supra-threshold muscle activation (overt movement execution) or motor inhibition (absent motor output, the result evaluated as similar to motor imagery). From there it requires a considerable amount of energy to reach the state of quasi-movements again. For further possible theoretical and computational applications of quasi-movements in this sense, compare e.g. Abraham and Gilgen (1995), Heath (2000), Kriz (1999), or Thelen and Smith (1994), all with emphasis on the neurocognitive domain.

In fact, this hard to-reach state is reflected in what subjects report and what is also experienced during one’s own performance of quasi-movements. They are more demanding to accomplish in terms of effort and concentration, when integrating two initially conflicting motor commands and keeping the balance between both.

Results of the present study show that the strength of proprioceptive feelings was larger in quasi-movements than in motor imagery. But importantly, there was no significant correlation between the amount of motor output (EMG detection rate) and the subjective evaluation of proprioception, thus indicating that the presence of occasional, subliminal muscle activity in “quasi” and “imag” sessions was not crucial for the subjective judgment. So what might be then the reason for a stronger perception during quasi-movements? It has been intensively debated that the conscious sense of a movement is not only associated with peripheral feedback but also with the efference copy of the motor command (see above), thus being centrally elicited. TMS experiments demonstrated a sense of movement where muscle activity and proprioceptive feedback was blocked by temporary ischemia (Amassian, Cracco, & Maccabee, 1989) or where TMS of the motor cortex induced phantom hand movements in the amputated limb (Bestmann, Oliviero, Voss, Dechent, Lopez-Dolado, Driver, & Baudewig, 2006). These results indicate the existence of an efference copy in absence of reafferences from the periphery. Efference copy also strongly affects the subjective evaluation of the overtly performed movements (Farrer, Franck, Paillard, & Jeannerod, 2003; Haggard, 2005; McCloskey, Colebatch, Potter, & Burke, 1983).

In these studies it was emphasized that it is not the efference copy *per se* which is responsible for the conscious sense of the movement, it is rather a complex interplay between the sensory predictions of the upcoming movements and the actual sensory feedback, mediated by "a mental process which binds intentional actions to the external events that they produce" (Haggard, 2005, p. 294; "intentional binding", Tsakiris & Haggard, 2003; Wolpert & Ghahramani, 2000). In case of quasi-movements the predicted zero-feedback (by a forward model of the movement) would be congruent with usually absent sensory signals from the periphery; this correspondence might also result in a sense of agency (Farrer et al., 2003; Haggard, 2005).

5.4 Intention, quasi-movements, and motor imagery

At a certain point during the performance of quasi-movements a stage is reached where no muscle force is produced anymore or it is comparable to the force produced during pure motor imagery. This was confirmed by the absence of significant differences between post-stimulus interval EMG activity for "quasi" and "imag" condition, as well as by insignificant fluctuations in pre- and post-intervals demonstrated by within-subject comparisons for each condition. Although objectively both conditions were not distinguishable, one of the main differences between imagery and quasi-movements is that the latter are *intended* as overt movements (Haggard, 2005), contrary to the former where subjects were fully aware that the movement should be only *simulated* (Jeannerod, 1994, 1995; 2001; Michelon, Vettel, & Zacks, 2006). Indeed, motor imagery, "defined as mental simulation of a movement" (Neuper et al., 2005, p. 668) or "in the most general sense… [referring] to the 'mental rehearsal of simple or complex motor acts that is not accompanied by overt body movements'" (Solodkin et al., 2004, p. 1246), does not have the explicit goal of executing a movement, regardless of whatever muscle force involved. "Motor imagery is no longer imagery when the musculature is activated. Motor imagery is a cognitive process that engages a variety of supraspinal structures, without resulting in any outflow from the spinal motorneuron pool" (Stinear et al., 2006, p. 158). But contra-intuitively, (kinesthetic) motor imagery often involves subliminal motor output and also proprioceptive sensations (compare "psychoneuromuscular effects", "ideo-motor principle"; Jacobson, 1932; Guillot & Collet, 2006; Martin, Moritz, & Hall, 1999; Shaw, 1938; Stock & Stock, 2004); a fact also evidenced by results of our study. Nevertheless, these involuntary motor responses of "imag" condition differed quantitatively and qualitatively from quasi-movements, where in occasional trials one could clearly see a series of low-amplitude EMG bursts, which were comparable to the performance in "real" condition in their timing and frequency (though definitively not in force). In this respect it is unlikely that only preparation to motor action might constitute the basis for quasi-movements since subjects were actively "performing" the movements, also reflected by a significantly higher detection rate in EMG compared to "imag" condition.

But stating it explicitly, quasi-movements are neither “real” movements nor motor imagery. They provide a novel kind of cognitive and (neuro-) physiological experience, where both aspects somehow merge to a qualitatively new state. During the performance of quasi-movements one has the subjective impression of “imagery” and “reality” being blurred and one cannot tell on what “side” they should be placed; this experience was demonstrated in the present study as revealed by consistently intermediate task ratings on the “reality index”. This result reminds of William James’ considerations upon “if a sensation of sound were only a strong imagination, and an imagination a weak sensation, there ought to be a *border-line of experience* where we never could tell whether we were hearing a weak sound or imagining a strong one” (James, 1890, chapter 18; italics added). Simply substituting with “sound” with “movement” and “hearing” with “feeling” and it is an appropriate description how quasi-movements are experienced. Important to note is also the high correlation between reality indices of “quasi” and “imag” conditions (ρ=0.71, P<0.002).

Subjects spontaneously report that quasi-movements “feel like imagery”, referring to the fact of absent or subliminal peripheral feedback; this is also reflected in the strong significant correlation between reality indices of both conditions. Still their performance has the objective “external” state of a “real” motor action with infinitively minimized movement strength, since quasi-movements are learned via gradual decrease of muscle force; the intention of true motor execution is kept, also when efferent and afferent signals are absent. This is also reflected in spontaneous remarks of subjects, stating with emphasis that they are convinced of truly performing movements (“I’m *feeling* doing it!”).

In this respect, quasi-movements could provide an interesting paradigm to explore further the assumption of a continuity between movement execution and motor imagery. The basic idea of a continuity assumption is that motor imagery “is simply a sub-threshold arousal of the normal motor output system which is [in some instances] sufficiently strong to generate kinaesthetic sensations” (Annett, 1995, p. 162), which incorporates the activation of central motor plans. Kinesthetic motor imagery is conceived as a neural *simulation* of executed movements, whereby motor images are conceived as very weak (subthreshold) motor actions (Jeannerod, 2001). The examined parameters during motor imagery should resemble those occurring during actual motor performance of the same task, but with weaker expression; a consideration confirmed by a large number of studies addressing central and peripheral neurophysiological processes (Deschaumes-Molinaro, Dittmar, & Vernet-Maury, 1992; Decety, 1996; Guillot & Collet, 2005; Li, Kamper, Stevens, & Rymer, 2004; Lotze & Halsband, 2006; Oishi, Kasai, & Maeshima, 2000; Sharma, Pomeroy, & Baron, 2006; Solodkin et al., 2004; Wang & Morgan, 1992). The concept of quasi-movements is consistent with these mentioned aspects; but importantly they differ in their goal and performance acquisition from motor imagery, being conceptually closer to actual motor execution.

5.5 Neurophysiological bases of quasi-movements

Our data show that the topography of neuronal activity (evident from CSP analysis) during the performance of quasi-movements did not deviate significantly from motor imagery and movement execution. This is consistent with the above mentioned studies demonstrating that real and imagined movements share similar networks in a variety of structures like secondary and primary motor areas, prefrontal and parietal areas, as well as in subcortical regions like basal ganglia, cerebellum and at spinal levels. It is assumed that "motor imagery and motor execution overlap in their computational features and in their neural substrates" (Michelon et al., 2006, p. 811). Imagined and prepared or executed "real" actions are *functionally equivalent* (Jeannerod, 1994); furthermore, motor imagery can be considered "as being functionally equivalent to physical objects or events, with respect to certain types of outcomes", like "perceptual and behavioral effects" (Finke, 1980, p. 113, here applied to motor imagery). ERD in the alpha/mu-range over sensorimotor areas can be shown during imagined, prepared, executed – and now also for quasi-movements. Although spatial distribution of neuronal activity appeared to be similar between our three task conditions, the strength and laterality of ERD differed significantly. Its deflection in quasi-movements ranged at an intermediate level between "imag" and "real" condition. This might be explained by a number of aspects. Although quasi-movements are associated with zero force and no actual trajectory, subjects still were trying to perform the thumb abduction presumably into a specific *direction*. Therefore neuronal activity might be largely related to the coding of more global movement aspects like its direction (Andersen & Buneo, 2002; Buneo, Jarvis, Batista, & Andersen, 2002, Cisek, Crammond, & Kalaska, 2003; Georgopoulos, Schwartz, & Kettner, 1986). Neuronal activity in the primary cortex has been shown to be correlated with the produced movement force (Ashe, 1997; Evarts, 1968). A number of EEG studies also show that movement related potentials, generated in sensorimotor cortex, are correlated with force production (Kutas & Donchin, 1974; Slobounov, Ray & Simon, 1998). However, since the amplitude of motor potentials is only partly generated in sensorimotor cortex it is not clear *what else* constitutes the major part of these potentials. In this respect it is important to note that the neuronal activity in primary motor cortex is also highly correlated with other parameters of the task like movement direction or hand position (Kakei, Hoffman, & Strick, 1999; Sergio & Kalaska, 2003) – the parameters which still can be coded in quasi-movements and thus strongly modulate spontaneous EEG activity, as observed in the present study.

Our careful analysis of the relation between EMG and EEG data shows that even if occasional motor output is present in "quasi" condition this does not significantly influence ongoing neuronal activity (also true for "imag"). ERD and amplitude of EMG activity during task performance are in most cases uncorrelated, and even if in *some* subjects these correlations were significant, they were of weak strength. Contralateral ERD is also not significantly correlated to the relative amount of motor output across the sessions (determined by the EMG detection rate). EEG can discriminate very accurately between left and right movements, whereas EMG in "quasi" and "imag" conditions cannot. Furthermore, employing sophisticated analysis tools from BCI research results in a quantitative measure of this discrimination, the classification error. Its size does not depend on the amount of trials with detectable motor output, as our study demonstrates. These results indicate that EMG does not causally influence EEG activity and that neither motor imagery nor quasi-movements rely on bottom-up processes like peripheral muscle activity or sensory feedback, they are rather centrally driven. Still the interesting question remains how then and if at all the brain "differentiates" between imagery and reality.

Another topic of interest is the crucial role of motor inhibition in quasi-movements. The absence of responsive muscle activity in EMG is considered crucial for the demonstration of the purely central origin of motor imagery. It might be hypothesized that during quasi-movements similar or even identical inhibitory neuronal mechanism are engaged as during motor imagery, whereby in the latter case "the neural generator(s) of such inhibitory signals have not yet been identified" (Michelon et al., 2005, p. 819). In this respect all stations ranging from cortical regions to the motor neurons are potential candidates. Selective action inhibition mechanisms of cortical origin (cortico-cortical and cortico-spinal) may involve prefrontal areas like the middle frontal or inferior frontal gyrus, orbito-frontal areas or the cingulated, the thalamus, the basal ganglia or the cerebellum. Especially inhibition within primary motor cortex is in question, perhaps due to influences by supplementary motor areas, premotor cortex or superior parietal lobe. In any case, the selective inhibitory functions brain regions at cortico-cortical levels "should not be confounded with the more global descending inhibition of motor commands… at the spinal level" (Jeannerod, 2001, p. 107). There, these two proposed inhibitory mechanisms may work in parallel (Jeannerod, 2001; Michelon et al., 2005; Sharma et al., 2006).

The point here is that both tasks, motor imagery and quasi-movements, occasionally involve subliminal motor output. Though in one case these movements are intended and sometimes escape their conscious, active inhibition which has to be actively learnt. In the second case motor responses are blocked by default, and their incomplete inhibition is rather a "side-product" since motor imagery engages similar or identical networks of the motor system as actual movement execution. Although also imagery skills can be improved by training (Hall & Martin, 1997), usually one somehow "knows" how to do motor imagery. In our study subjects did not need 15 or 30 minutes training in order to laboriously learn how to imagine a movement. However, *what exactly* our subjects did during "imag" condition we cannot know and we rely on the subjects' compliance to the task. The case is different with quasi-movements, as already mentioned above.

5.6 Performance of movements without executing them: BCI application

Quasi-movements are consistent with common definitions of (kinesthetic) motor imagery: "A general feature of motor imagery is that subjects *feel* they are performing a certain movement without executing it" (Li et al., 2004, p. 9674; italics added). It is defined as "the ability to imagine performing a movement without executing it (Michelon et al, 2006, p. 811). The latter part, starting from "performing", in fact describes what quasi-movements actually are. As motor imagery they do not involve motor output, or only sometimes to a minor extent.

Task instructions

Motor imagery is elicited by verbal or written instructions and/or in comparison to physical demonstration/execution of the supposed motor action. For experiments with BCI, the subject's brain activity is recorded in a number of sessions during motor imagery of the selected movement. This data is classified offline and the obtained classifier parameters are used for online feedback applications. As already mentioned above , attenuation of spontaneous oscillations in the alpha range (also in central beta rhythms), more precisely in arch-shaped Rolandic mu-rhythms (~ 8–13 Hz), recordable over sensorimotor cortices, can be demonstrated by somatosensory stimulation, motor preparation and observation, voluntary movement, and motor imagery (Chatrian, Petersen, & Lazarte, 1959; Gastaut & Bert, 1954; Jasper & Penfield, 1949; Michelon et al., 2006; Pineda, 2005; Pfurtscheller et al., 2006; Pfurtscheller, Neuper, Brunner, & Lopes da Silva, 2005). In an experiment concerned with motor imagery or BCI, giving task instructions to the subject is one of the most delicate stages. Instructions are *the* mean to mediate the correspondence between task objectives and subject's performance, and they do account to a great deal for large variability in the results. Here the exact wording is important: the instruction should be standardized, precise, and comprehensible, formulated according to subjects' population. Furthermore, the instruction should specify the intended imagery perspective (like kinesthetic or visual motor imagery), exclude the use of alternative cognitive strategies like internal counting or visual imagery, and determine the context of the imagined movement (ideally, in kinesthetic motor imagery without external *visual* contextual reference, which would confound extremely the designated imagery performance). Unfortunately, the task instructions are quite often inconsistent, imprecise, unspecified according to the imagery perspective, not exclusive, or even not reported in study papers (Sharma et al., 2006; see examples for inaccurate instructions e.g. Stinear et al., 2006; Lotze, Montoya, Erb, Hülsband, Flor, Klose, et al., 1999; Michelon et al., 2006). It is unclear then how carefully the instructions were given in the respective study and on what motor imagery type the conclusions and results are based. Of course, accurate control over an internal, subjective process remains principally impossible, but it might be approached by precise instructions, which would in general follow the structure of: *how* to imagine *what*, and *what not*. We were clearly aware of this fact, so that in the present study these requirements are met with the given instructions for motor imagery (cf. Appendix A). But so far, another principle problem with given task instructions for motor imagery is the following: they require an existing or intuitive knowledge how to actually do motor imagery: "*Imagine* moving your right thumb" – this is how instructions are formulated in a nutshell. Thus, the cognitive and (neuro-) physiological state for motor imagery is reached by an abstract semantic circumscription using "to imagine" or "imagination/imagery" (circular definition problem). Quasi-movements provide a fascinating way to reach an internal cognitive state, without relying on circumscriptions by "imagery" or "real", which is evaluated in its result as *similar* to motor imagery. But moreover, "quasi" task was always rated as more "real" than imagery itself (as measured by the "reality index"). By common vividness ratings in standard questionnaires (Galton, 1880, 1883; Cumming & Hall, 2002; Hall & Pongrac, 1983; Hall & Martin, 1997; Isaac, et al., 1986; Marks, 1973; Martin et al., 1999; Moran, 1983; Richardson, 1994; Sheehan, 1967; Sheik & Jordan, 1983) this would indicate an improvement in imagery abilities. In this respect, imagery abilities as assessed by the QMI and the VMIQ neither significantly correlated with the classification error in "imag" and "quasi" tasks, nor were they correlated with the amount of ERD. So far, studies addressing BCIs based on spatio-spectral changes related to motor imagery have not reported upon the relation between imagery ability questionnaires and performance parameters for BCI purposes (like classification error or information transfer speed). Our results indicate that paper-and-pencil questionnaires aiming at the assessment of general imagery ability do not provide a reliable predictor for BCI purposes (a critical discussion of their design, validity and reliability is beyond the scope of the present study); other cognitive variables have been shown to be of more relevance (Burde & Blankertz, 2006; Mahmoudi & Erfanian, 2006).

Improvement of BCI classification accuracy by quasi-movements

But to state it explicitly again, quasi-movements are definitively *not* motor imagery, because they are derived from and intended as actual movement execution. Nor they are "real" movements: When performed properly, they do not involve detectable motor output and are not confounded by proprioceptive, visual or tactile feedback; whereby task performance is precisely specified and controllable. In this sense quasi-movements are less abstract than imagined actions, also since they address (so far) only one specific muscle with a minimized ballistic movement. Therefore quasi-movements would be related to a more specific and stronger activation of the motor network, which is consistent with our finding that they showed larger ERD compared to motor imagery.

Still the question remains why and how exactly they lead consistently to a classification improvement in terms of reduced error rates – a topic which was not the primary objective of the present study and will be addressed with future studies. With respect to practical applicability of quasi-movements, one of the most striking findings of our study is the *relative* improvement in classification accuracy of "quasi" compared to "imag" task. This is demonstrated by the relative error reduction of 54% on average – with the largest error drop of 86% in a single subject (S11). In this case, the amount of *correctly* discriminated data into left and right movement class even reached 96% for "quasi" condition. This improvement cannot be attributed to peripheral muscle activity or reafferent feedback, as our results clearly evidence. When EEG single trial classification was run only on those trials which do not contain detected motor responses, instead of using all available trials, the obtained error for "imag" and "quasi" condition changes only fractionally and the difference between both remains highly significant. Consequently, classification of silent EMG trials was only on chance level, without significant differences between both conditions.

An alternative way to study muscle activity would be to use needle electrodes to record EMG from the individual muscle fibers, yet it would not be optimal since in case of absent movement it is almost impossible to find active muscle fibers. Even assuming that there might have been some subliminal muscle activity left undetected, the main finding in the present study relates to the fact that muscle activity in quasi-movements is as small as during motor imagery.

Furthermore, the general classification improvement in EEG was especially true for subjects with high classification errors for "imag" and relatively low erroneous classification in "real" condition; those subjects who initially represented the target group for the aim of developing an alternative strategy to usually employed motor imagery in ERD-based BCIs.

Another interesting side-aspect indicates the importance and usefulness of quasi-movements in this practical application. In three subjects (S8, S11, S16) who had previous experiences with online BCI and had shown comparably insufficient classification accuracies and/or unsatisfactory online performance (low information transfer rates), quasi-movements led in all three subjects to an greatly reduced classification error, and in two cases also to improved online performance. Another possible approach would be to explore the brain dynamics during quasi-movements in a self-paced (uncued) condition and also utilizing lateralized readiness potentials (Jankelowitz & Colebatch, 2002) for BCI purposes (Blankertz, Dornhege, Krauledat, Müller, et al., 2006).

Relevance for subjects with disabilities

On the practical level quasi-movements provide an alternative and effective strategy for non-disabled subjects in BCI context. Moreover, the paradigm provides another advantage "because one potential BCI-application is with paralysed patients, [and] one might consider to mimic the >no-motor-output< of these individuals having healthy experimental subjects to intend a movement but to withhold its execution (*motor imagery*)" (Blankertz, Curio, & Müller, 2002, p. 158; italics in original). When formulated some years ago, this goal of mimicking the "no-motor-output" was described as being achievable through using motor imagery, what is to date a standard strategy in BCI context. But conceptually it does not meet exactly the formulated requirements: "to intend a movement but to withhold its execution". As already mentioned above, during motor imagery non-disabled subjects are fully aware of the fact that they should mentally *simulate* a movement (and of course not to perform it), so that they do not explicitly *intend* its execution. Therefore, when studying non-disabled subjects during brain-computer interaction and wanting to generalize study results (at least to a certain extent) to subjects' population with paralysis or amputations, then quasi-movements capture their performance more accurately than motor imagery does. Disabled subjects *try* to perform "real" movements; they *intend* to do so without merely imagining or simulating them (Blankertz et al., 2006). Although these subjects cannot aim at *minimizing* movement strength to zero motor output, at least the *intention* to move is captured during the performance of quasi-movements (and absent motor responses). Therefore, in application with non-disabled users our paradigm is closer to the situation of individuals with disabilities than when using motor imagery as strategy, especially in BCI context.

The following arguments in summary serve as evidence that subjects were indeed performing movements and *not* imagining them in “quasi” condition: (1) The most important point is that all but one subject reported that they were executing a movement (though not visible to the external observer). (2) It took subjects up to 30 minutes to learn to perform quasi-movements, while motor imagery could be performed right away without any training. (3) The detection rate of EMG was significantly higher in “quasi” compared to “imag” condition. (4) Traces of EMG in “quasi” sessions sometimes consequent spikes corresponding to a series of movements, thus showing compliance of the subjects with the task’s instruction. (5) ERD was stronger and classification error smaller in “quasi” condition compared to “imag”.

5.7 Future perspectives for the study of quasi-movements

However, after the initial exploration of neuronal activity for quasi-movements, the precise determination of the network’s temporal, spatial and interactive characteristics should be objectives of subsequent studies, incorporating EEG, functional magnetic resonance imaging, TMS, or combination of these methods. Another study objective should be the characteristics of evoked responses related to the performance of quasi-movements. Computational modeling of the transition between executed “real” movements to the performance of quasi-movements could reveal more detailed the functioning and learning/adaptation processes of the motor system, especially in the context of ambiguous performance goals.

Furthermore, careful analysis of EMG data should always be implemented as the most crucial means to determine successful acquisition of quasi-movement and subject’s compliance during task performance. A special study objective will be the characteristics of occasional motor output when muscle activity is not successfully blocked. When, how, and why do these EMG bursts occur? Do they reflect a departure from the sensitive equilibrium balancing excitatory and inhibitory motor commands? In what way is this related to cognitive factors like concentration, attention, motivation, or previous training experience with quasi-movements? Are they subjectively perceived as more demanding and exhausting than motor execution and imagination, because in the latter cases conflicting task goals are missing, with respect to motor imagery, where inhibition of movement execution is a rather automatic process, which thus requires a minor deal of resources compared to quasi-movements, where movement inhibition needs to be actively learnt?

Exactly this learning process provides another interesting study topic: what are optimal training conditions (length, intervals, rewards, feedback characteristics, environmental context) and how does the paradigm of quasi-movements fit into the context of learning principles like operant conditioning? Moreover, do individual differences exist in the acquisition and performance accuracy (measured as zero or close to-zero EMG detection rate)? And how do neuronal dynamics behave in the long-term perspective? It might be possible that the observed characteristics of brain activity in our study diminish, remain unchanged or are strengthened with further training of quasi-movements.

The study of quasi-movements can be extended from the so far simple movement of thumb abduction, involving only one muscle, to more complex movements which comprise a greater number of target muscles, also involving different body limbs. In any case it should be again emphasized that both objective and subjective approaches are required for an adequate study of quasi-movements. Another aim should be the development of more elaborated measure instruments assessing the subjective evaluation and experience of the task performance.

Finally, to arrive at the initial starting point from which the paradigm of quasi-movements was developed: how and why do they change oscillatory neuronal activity more pronounced than motor imagery, so that performers improve classification accuracy in BCI context?

One of the most striking questions is: what is different in the brain activity from subjects benefiting from quasi-movements which have high classification errors for imagery?

Why is subject S11 able to reduce the initially high error for “imag” (28%) to incredible 4% by quasi-movements? Remarkable since comparable 2% of misclassifications were achieved by “real” movement execution. Yet, quasi-movements had almost *zero* motor output and thus fulfilling the criteria necessary for operating a BCI, as demonstrated by an EMG detection rate of approximately 0.05 for “imag” and “quasi” condition. Meaning that in only 5% of the trials motor responses could be detected, which moreover were not significantly related to stimulus presentation. Please refer to Figures A2-3 and A5–9 in the appendix for comparing EMG and EEG data. This subject has been chosen for complete display purposes because of having the highest benefit from the performance of quasi-movements (86% error reduction) and simultaneously the lowest erroneous classification rate for “quasi” condition.

The results for S11 are one demonstration of our general finding that quasi-movements can be used as an (very) advantageous alternative to motor imagery strategies for BCI purposes, especially for subjects showing insufficient classification accuracy with usual motor imagery strategies. In this sense and in contrast to prevailing approaches, quasi-movements provide very simple and powerful tool that does not require previous imagery experiences or high imagery abilities or extensive training. They can be learned in relatively short time and are derived from an externally controllable motor task.

Our results provide clear evidence for improved offline classification (calibration/training period), which is the prerequisite for (successful) online feedback. Therefore it is of tremendous interest how quasi-movements behave in online brain-computer interaction and whether they bridge the offline-online gap (Shenoy et al., 2006). Preliminary self-experience with quasi-movements in BCI application highly supports this notion, and it will be the objective of further studies to explore its experimental verification.

„A poet once said 'The whole universe is in a glass of wine'… it is true that if we look at a glass closely enough we see the entire universe… If our small minds, for some convenience, divide this glass of wine, this universe, into parts - physics, biology, geology, astronomy, psychology, and so on - remember that Nature does not know it! So let us put it all back together, not forgetting ultimately what it is for. Let it give us one more final pleasure: drink it and forget it all!"

(Richard P. Feynman (1963), Lectures on Physics, Volume 1, Chapter 3)

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VII. APPENDICES

Appendix A: Verbal task instructions

MOVEMENT EXECUTION
Perform an abduction of your thumb. Let this movement be relatively weak, but clearly visible.

On the screen the letters "L" and "R" will appear in random order for 3 seconds in duration. During this time, perform the thumb movement with your left hand when "L" appears and with your right hand for "R". Keep the other hand as relaxed as possible. Do the movements with a frequency of 2 Hz, that is, approximately 5-6 movements during 3 seconds. As soon as the letters disappear from the screen, stop moving immediately and relax both hands during the short breaks between the trials, which will last for about 2 seconds.

During the session, keep your eyes always fixated on the cross in the middle of the screen.
The experimenter will tell you during the session, when your hands are tensed. Try not to blink too much, especially not to the beginning or end of a stimulus.

KINESTHETIC MOTOR IMAGERY
Imagine an abduction of your thumb from a first-person perspective. Imagine the movement being relatively weak, but pronounced. Concentrate on the initiation and the performance of the movement, without trying to visualize or to "feel" (tactile) your moving hand. Also avoid internal counting of your movements.

On the screen the letters "L" and "R" will appear in random order for 3 seconds in duration. During this time, imagine performing the thumb movement with your left hand when "L" appears and with your right hand for "R". In each case, imagine doing the movements with a frequency of 2 Hz, that is, approximately 5-6 movements during 3 seconds. As soon as the letters disappear from the screen, stop imagining immediately and rest during the short breaks (which will last for about 2 seconds) without thinking of something in particular.

During the session, keep your eyes always fixated on the cross in the middle of the screen.
The experimenter will tell you during the session, when your hands are tensed. Anyway, keep on telling yourself to relax your hands. Try not to blink too much, especially not to the beginning or end of a stimulus.

QUASI-MOVEMENTS
Perform an abduction of your thumb and let this movement be relatively weak. Now try to minimize this small movement even further and make your movements as small as it is possible for you.

1) Training with visual feedback (EMG traces)
On the screen you see the traces of your own muscle activity (EMG) of the left and right hand, respectively. On the x-axis you see the time course; on the y-axis you see the amplitude, that is, it reflects the "strength" of your produced muscle activity.
Now try to make the peaks smaller, until they are undistinguishable from background EMG (which is not related to your *deliberate* muscle activity).
For the first round, do only one or two movements at once, you can execute them slowly and consciously. During the next rounds, you will be able to speed them up. Do not be irritated if you cannot see your thumb moving anymore, the EMG reflects reliably the strength of your muscle activity. Try to concentrate intensively on this task, because it requires much effort to reduce your muscle activity to a minimum. Keep the other hand as relaxed as possible.

% wait until subject is able to produce motor responses which are barely above or undistinguishable from baseline activity %

2) Training with verbal feedback by the researcher (without showing EMG)

Continue trying to make your movements as weak and small as possible. Now you will perform this task without visual feedback; that is for being able to concentrate better on your task, and the experimenter will give you feedback by telling if your movements are strong or weak.

When the experimenter tells you “left” or “right”, do 1 movement only.

% wait until motor responses are barely above or undistinguishable from baseline activity %

When the experimenter tells you “left” or “right”, do 3 fast movements after, then stop until the next command.

% wait until motor responses are barely above or undistinguishable from baseline activity %

When the experimenter tells you “left” or “right”, do 6 fast movements, then stop until the next command.

% wait until motor responses are barely above or undistinguishable from baseline activity %

Now you will be given a training period to get used to your task while performing it in the experimental recording session. When seeing “L” or “R” on the screen, perform these infinitively small movements with a speed of about 2 Hz, that is, approximately 5-6 movements during 3 seconds. As soon as the letters disappear from the screen, stop performing and rest during the short breaks, which will last for about 2 seconds.

Before starting recordings

Try to memorize the way you have performed these very small movements, try to internalize this state you have been trained in. During seeing “L” or “R” on the screen, perform the infinitively small movements with a speed of about 2 Hz, that is, approximately 5-6 movements during 3 seconds. Keep the other hand as relaxed as possible. As soon as the letters disappear from the screen, stop performing immediately and rest during the short breaks between the trials, which will last for about 2 seconds.

During the recording session keep your eyes always fixated on the cross in the middle of the screen. If we see any strong EMG response we will inform you during the session, so that there will be two types of commands: “smaller on the right/left side” and “relax right/left hand” when you unconsciously tensed your muscles. Do not respond verbally to the commands, and always keep on telling yourself to relax your hands.

German versions (translations by the author) of the task instructions and task ratings, of the QMI, VMIQ, and Oldfield’s handedness inventory are available upon request (F.U.Hohlefeld@web.de).

Appendix B: Task ratings

Part A: Ratings for each of the three experimental conditions. Subjects were not shown their respective former ratings. Note that questions 3 and 4 were only presented in quasi-movements condition.

Part B: Final ratings after recording all three conditions.

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gender: …. male …. female

age: …… years

birthday (day-month-year): … … …

current occupation: ……………………….

Please take your time to have a look at the following questions.
Remember: All your data will be kept anonymously. There are no “right” or “wrong” answers.

1) What does “imagination” mean to you?
Below you see a collection of some related and unrelated expressions, and we would like you to choose three terms out of each category. Just cross them, and if among available ones some are missing for you, write your own choices beneath the table.

related expressions	unrelated expressions
seeing in the mind's eye	truth
unconsciousness	reality
creativity	action
idea	perception
fantasy	objective existence
hallucination	observation
unreality	actuality
mental rehearsal	facts

or maybe something else missing above?

………………………… …………………………
………………………… …………………………

2) And how would you define intuitively “imagined” and “real” movements?

…………………………………………………………………… imagined movement
…………………………………………………………………… real movement

If you are aware of a more “scientific” definition and would like to prefer this:

…………………………………………………………………… imagined movement
…………………………………………………………………… real movement

Part A

1) To what extent have you executed the movement (produced muscle activity), that is, to what extend could you feel your muscle moving inside?

1	2	3	4	5

no muscle activity full muscle activity

2) To what extent has it been “real”, “imagined”, or something in between for you? Please cross at the appropriate place.

real ◆———————————◆ imagined

3) If the distance, marked with two arrows, is the maximal strength of your movement, how much “smaller” were you able to make it?
Please estimate the size and cross the appropriate distance.

min. ◄———————————► max. strength

4) Were you trying to do real movements? ___ YES ___ NO, but: ………………

Part B

1) Please rank the previous 3 tasks according to their degree of “reality”, that is, how much “real” or “imagined” aspects they contained for you.

mainly IMAGINED ……………….
……………….
mainly REAL ……………….

2) Which was for you the most demanding task (in terms of effort and concentration)?

MOST demanding ……………….
……………….
LEAST demanding ……………….

3) When you were performing those very small (invisible) movements and you were instructed to make them smaller, do you think at some point that the experimenter was playing tricks on you?

___ NO
___ YES, because/when: …………………………………………………………..

German versions (translations by the author) of the task instructions and task ratings, of the QMI, VMIQ, and Oldfield’s handedness inventory are available upon request (F.U.Hohlefeld@web.de).

Appendix C: Questionnaires
QMI – Questionnaire Upon Mental Imagery (Sheehan, 1967)

Items	*Modality*
1. The exact contour of face, head, shoulders and body	
2. Characteristic poses of head, attitude of body, etc.	
3. The precise carriage, length of step, etc. in walking	
4. The different colours worn in some familiar costume	
5. The sun as it is sinking below the horizon	*visual*
6. The whistle of a locomotive	
7. The honk of an automobile	
8. The mewing of a cat	
9. The sound of escaping steam	
10. The clapping of hands in applause	*auditory*
11. Sand	
12. Linen	
13. Fur	
14. The prick of a pin	
15. The warmth of a tepid bath	*cutaneous*
16. Running upstairs	
17. Springing across a gutter	
18. Drawing a circle on paper	
19. Reaching up to a high shelf	
20. Kicking something out of your way	*kinesthetic*
21. Salt	
22. Granulated (white) sugar	
23. Oranges	
24. Jelly	
25. Your favourite soup	*gustatory*
26. An ill-ventilated room	
27. Cooking cabbage	
28. Roast beef	
29. Fresh paint	
30. New leather	*olfactory*
31. Fatigue	
32. Hunger	
33. A sore throat	
34. Drowsiness	
35. Repletion as from a very full meal	*organic*

Rating scale:

The image aroused by an item of this test may be:

Perfectly clear and as vivid as the actual experience	Rating 1
Very clear and comparable in vividness to the actual experience	Rating 2
Moderately clear and vivid	Rating 3
Not clear or vivid, but recognizable	Rating 4
Vague and dim	Rating 5
So vague and dim as to be hardly discernible	Rating 6
No image present at all, you only “knowing” that you are thinking of the object	Rating 7

VMIQ – Vividness of Movement Imagery Questionnaire (Isaac, Marks, & Russell, 1986)

Items
1. Standing
2. Walking
3. Running
4. Jumping
5. Reaching for something on tiptoe
6. Drawing a circle on paper
7. Kicking a stone
8. Bending to pick up a coin
9. Falling forwards
10. Running up stairs
11. Jumping sideways
12. Slipping over backwards
13. Catching a ball with two hands
14. Throwing a stone into water
15. Kicking a ball in the air
16. Hitting a ball along the ground
17. Running downhill
18. Climbing over a high wall
19. Sliding on ice
20. Riding a bike
21. Jumping into water
22. Swinging on a rope
23. Balancing on one leg
24. Jumping of a high wall

Subscale 1: external, third-person perspective (visual motor imagery)
"Imagine watching somebody else"
Subscale 2: internal, first-person perspective (kinesthetic motor imagery)
"Imagine doing it yourself" → *used in the present study*

Rating scale:

The image aroused by each item might be:

Perfectly clear and vivid as normal vision	…….. Rating 1
Clear and reasonably vivid	…….. Rating 2
Moderately clear and vivid	…….. Rating 3
Vague and dim	…….. Rating 4
No image at all, you only "know" that you are thinking of the skill	…….. Rating 5

German versions (translations by the author) of the task instructions and task ratings, of the QMI, VMIQ, and Oldfield's handedness inventory are available upon request (F.U.Hohlefeld@web.de).

Appendix D: Tables

Table 1. *Statistics of task ratings and imagery-ability questionnaires*

Variable		*MEAN*	*SD*	*SEM*	*N*
QMI (s.u.)	all scales	2.61	0.75		17
VMIQ (s.u.)	kinesthetic scale	2.15	0.60		17
	real	98.72	3.73	0.93	16
Reality index (%)*	quasi	55.65	23.26	5.82	16
	imag	19.00	21.66	5.41	16
	real	4.31	0.79	0.20	16
Proprioception (s.u.)**	quasi	2.75	1.24	0.31	16
	imag	1.88	0.96	0.24	16
Subjects	age	29.12	6.80		17
	gender	9 males, 8 females			
	handedness	13 right-handed, 4 left-handed			
	native language	12 German, 5 non-German			

* compare with Figure 1; ** compare with Figure 2

Note:
s.u. – scale units
SD – standard deviation
SEM – standard error of the mean
real – movement execution
quasi – quasi-movements
imag – kinesthetic motor imagery

QMI – Questionnaire Upon Mental Imagery (Sheehan, 1967)
rating 1= “Perfectly clear and as vivid as the actual experience”
rating 7= “No image present at all, you only “knowing” that you are thinking of the object”

VMIQ – Vividness of Movement Imagery Questionnaire (Isaac, Marks, & Russell, 1986)
rating 1= “Perfectly clear and vivid as normal vision”
rating 5= “No image at all, you only “know” that you are thinking of the skill”

Calculation of the “reality index” (RI; continuous scale):
RI=(scale length-rating value)/scale length*100
measured in cm; value of respective task rating measured from left side of the scale,
100% indicate that the task is evaluated as completely “real”, 0% as completely “imagined”

Evaluation of “proprioception” (discrete scale, 5 steps):
1=none, 5=strongest

Table 2. *EMG results – descriptive statistics*

Variable	Condition	Hand	*MEAN*	*SD*	*SEM*
Visually detected motor responses (µV)	real	BH	341.10	177.87	45.93
	quasi	BH	31.82	9.39	2.42
	imag	BH	27.31	9.44	2.44
Number of visually detected motor responses	real	BH	6.60	1.31	0.34
	quasi	BH	1.76	0.35	0.09
	imag	BH	1.38	0.17	0.04
Pre-stimulus interval (RMS µV)*	real	RH	3.85	3.62	0.93
		LH	3.98	2.43	0.63
Post-stimulus interval (RMS µV)*	real	RH	54.94	33.12	8.55
		LH	54.46	31.36	8.1
Pre-stimulus interval (RMS µV)	quasi	RH	1.92	0.57	0.12
		LH	2.28	1.05	0.27
Post-stimulus interval (RMS µV)	quasi	RH	1.92	0.58	0.15
		LH	2.32	1.1	0.28
Pre-stimulus interval (RMS µV)	imag	RH	1.74	0.44	0.11
		LH	2.08	0.95	0.24
Post-stimulus interval (RMS µV)	imag	RH	1.75	0.44	0.11
		LH	2.07	0.95	0.24
	real	BH	0.98	0.02	0.01
Detection rate**	quasi	BH	0.26	0.14	0.04
	imag	BH	0.14	0.07	0.02
N=15 for all calculations					
Number of subjects with significant detection rate	real	BH	*N*=15		
	quasi	BH	*N*=8		
	imag	BH	*N*=4		

* compare with Figure 4; ** compare with Figure 5

Note:
SD – standard deviation, SEM – standard error of the mean, RMS – root mean square
APB – abductor pollicis brevis
BH – both hands (values from left and right APB averaged)
RH/LH – right/left hand (right/left APB)
real – movement execution
quasi – quasi-movements
imag – kinesthetic motor imagery

Calculation of the EMG detection rate: detection rate=(RH+LH)/(trials_R+trials_L)
RH, LH: only right or left hand responses to stimulus “R” or “L”, respectively; no simultaneous responses; trials_R, trials_L: all trials for right or left hand=(108-epochs with artifacts); this ratio of the total number of detected correct motor responses to the total number of the presented stimuli should be close to zero for motor imagery, and 1 for actual movement execution. The obtained slightly smaller value for “real” can be the case because subjects might skip a few responses due to lacking attention or relaxation of their hand(s) in order to avoid excessive amount of baseline muscle activation.

Table 3. *EEG statistics*

Variable	Class and hemisphere	Condition	*MEAN*	*SD*	*SEM*
ERD (%)*	LH_ispi_(Lhm)	real	-29.72	18.53	4.95
	LH_contra_(Rhm)		-40.04	21.83	5.83
	RH_contra_(Lhm)		-42.81	21.78	5.82
	RH_ipsi_(Rhm)		-26.85	13.78	3.68
ERD (%)	LH_ispi_(Lhm)	quasi	-15.68	10.40	2.78
	LH_contra_(Rhm)		-31.54	18.70	5.00
	RH_contra_(Lhm)		-32.47	16.11	4.31
	RH_ipsi_(Rhm)		-14.37	9.72	2.60
ERD (%)	LH_ispi_(Lhm)	imag	-10.32	6.71	1.79
	LH_contra_(Rhm)		-23.67	15.2	4.06
	RH_contra_(Lhm)		-22.6	15.32	4.1
	RH_ipsi_(Rhm)		-12.1	7.61	2.03

N=14 for all calculations

* compare with Figure 6

Note:
ERD – event-related desynchronization
SD – standard deviation
SEM – standard error of the mean
RH – right hand movement (stimulus class “R”)
LH – left hand movement (stimulus class “L”)
Rhm/Lhm – right/left hemisphere
contra/ipsi – contralateral/ipsilateral
real – movement execution
quasi – quasi-movements
imag – kinesthetic motor imagery

<u>Calculation of ERD:</u>
ERD=(POST-PRE)/POST*100
POST=averaged electrophysiological activity in post-stimulus interval over channel with strongest ERD (70–3330 ms)
PRE=averaged electrophysiological activity in pre-stimulus interval over channel with strongest ERD (-500–0 ms)
negative values indicate the attenuation of spontaneous oscillations in the frequency range of 8–13 Hz in most reactive channels over central sensorimotor regions, positive values indicate an enhancement of these rhythms.

Table 4. *Single-trial EEG classification – statistics I*

Variable		Condition	*MEAN*	*SD*	*SEM*
Frequency band for automatic classification	lower limit	real	9.43	0.85	0.23
	upper limit		13.86	2.05	0.55
	lower limit	quasi	9.18	1.44	0.38
	upper limit		13.75	1.53	0.41
	lower limit	imag	8.57	1.64	0.44
	upper limit		13.36	1.39	0.37
Time interval for automatic classification	start	real	907	249	66
	end		3180	268	72
	start	quasi	669	224	60
	end		2936	418	112
	start	imag	562	178	48
	end		2572	576	154
Classification error*		real	0.08	0.08	0.02
		quasi	0.12	0.10	0.03
		imag	0.23	0.13	0.04
Classification accuracy (%)		real	92.21	8.35	2.23
		quasi	87.77	10.20	2.73
		imag	76.78	13.18	3.52

N=14 for all calculations

* compare with Figure 7

Note:
SD – standard deviation
SEM – standard error of the mean
real – movement execution
quasi – quasi-movements
imag – kinesthetic motor imagery

Calculation of the classification error:
ERROR=(misclassified trials/all classified trials)
0=correct classification of all trials
0.5=random classification (on chance level)

Calculation of the classification accuracy:
ACC=(1-ERROR)*100

Table 5. *Single-trial EEG classification – statistics II*

(a) Classification error

Subjects	ERROR_real	ERROR_quasi	ERROR_imag
S1	0.07	0.13	0.12
S2	0.22	0.40	0.49
S4	0.02	0.05	0.16
S5	0.29	0.24	0.33
S6	0.00	0.02	0.05
S7	0.02	0.10	0.20
S8	0.01	0.06	0.34
S10	0.09	0.16	0.34
S11	0.02	0.04	0.28
S12	0.03	0.00	0.07
S13	0.11	0.15	0.41
S14	0.09	0.14	0.17
S16	0.03	0.12	0.19
S17	0.10	0.12	0.13
MEAN *N*=14	0.08	0.12	0.24

* compare also with Figure 7.

Note:
real – movement execution
quasi – quasi-movements
imag – kinesthetic motor imagery

(b) Ranks for best classification (lowest error)

N=14		Conditions			Classification error	
Subjects	best	medium	poorest	ERROR_best	ERROR_medium	ERROR_poorest
*S1**	*real*	*imag*	*quasi*	*0.07*	*0.12*	*0.13*
S2	real	quasi	imag	0.22	0.40	0.49
S4	real	quasi	imag	0.02	0.05	0.16
S5	quasi	real	imag	0.24	0.29	0.33
S6	*real*	*quasi*	*imag*	*0.00*	*0.02*	*0.05*
S7	real	quasi	imag	0.02	0.10	0.20
S8	real	quasi	imag	0.01	0.06	0.34
S10	real	quasi	imag	0.09	0.16	0.34
S11	real	quasi	imag	0.02	0.04	0.28
S12	*quasi*	*real*	*imag*	*0.00*	*0.03*	*0.07*
S13	real	quasi	imag	0.11	0.15	0.41
S14	*real*	*quasi*	*imag*	*0.09*	*0.14*	*0.17*
S16	real	quasi	imag	0.03	0.12	0.19
S17	*real*	*quasi*	*imag*	*0.10*	*0.12*	*0.13*

* italics indicate subjects with insufficient modulation of classification accuracy between conditions, and were not included in the calculation for the mean improvement in classification accuracy of quasi-movements compared to motor imagery (compare Table 6.c below and Figures 8, 9)

(c) Absolute differences between classification errors

Subjects	DIFF_sorted*
14	*0.02*
5	*0.03*
1	*0.04*
10	*0.04*
12	*0.05*
4	0.06
3	0.09
13	0.11
6	0.12
8	0.17
9	0.17
2	0.18
11	0.2
7	0.22
N=14	

*compare with Figure 9

Note:
Calculation of the absolute difference between classification errors:
DIFF=(abs(real-quasi)+abs(real-imag)+abs(imag-quasi))/3
abs – absolute values

(d) Classification improvement by quasi-movements compared to kinesthetic motor imagery

Subjects	ERROR_real	ERROR_quasi	ERROR_imag	improvement (%)*
S2	0.22	0.40	0.49	18.08
S11	0.11	0.15	0.41	63.33
S7	0.01	0.06	0.34	**82.95**
S8	0.09	0.16	0.34	53.86
S4	0.24	0.29	0.33	28.46
S9	0.02	0.04	0.28	**86.38**
S6	0.02	0.10	0.20	49.36
S13	0.03	0.12	0.19	37.22
S3	0.02	0.05	0.16	**70.50**
MEAN	0.08	0.15	0.30	54.46
N=9				

* compare with Figure 9

Note:
Calculation of the classification improvement:
Improvement=(ERROR_imag-ERROR_quasi)./ERROR_imag*100

Table 6. *Correlations for EEG and EMG in three experimental conditions*

Correlation (Spearman)	Condition	% of significant correlations	*MEAN* of all coefficients	*SD*	*SEM*	*N*
	real	1.79	0.11	0.08	0.02	14
EEG vs. EMG RMS µV*	quasi	13.46	0.15	0.1	0.03	13
	imag	7.14	0.13	0.11	0.03	14
	real	96.43	0.72	0.19	0.05	14
EEG vs. class*	quasi	98.08	0.65	0.16	0.04	13
	imag	96.43	0.57	0.16	0.04	14
	real	100.00	0.96	0.09	0.02	14
EMG RMS µV vs. class*	quasi	26.92	0.19	0.16	0.04	13
	imag	7.14	0.09	0.09	0.02	14

* compare with Figures 11 and 12

Note:
EEG – mean amplitude of CSP components in post-stimulus interval (70-3500 ms)
RMS – root mean square of EMG amplitude in post-stimulus interval (70–3300 ms)
class – stimulus class: “L” left hand movement, “R” right hand movement)

Table 7. *Single-trial EMG and EEG classification – statistics*

(a) Classification error in EMG – all trials

Subjects	ERROR_real	ERROR_quasi	ERROR_imag
S1	0.00	0.49	0.51
S2	0.00	0.46	0.52
S4	0.00	0.37	0.38
S5	0.02	0.32	0.41
S6	0.00	0.25	0.55
S7	0.00	0.31	0.36
S10	0.01	0.47	0.46
S11	0.00	0.48	0.53
S12	0.00	0.31	0.44
S13	0.00	0.47	0.54
S14	0.01	0.49	0.51
S16	0.01	0.54	0.54
S17	0.08	0.43	0.50
MEAN error* *N=13*	0.01	0.41	0.48

* compare with Figure 14

Note:

Calculation of the classification error:
ERROR=(misclassified trials/all classified trials)
0=correct classification of all trials; 0.5=random classification (on chance level)

(b) Classification error in EMG – trials without visually detectable motor output

Subjects	ERROR_quasi	ERROR_imag
S1	0.59	0.59
S2	0.56	0.48
S4	0.46	0.57
S5	0.37	0.44
S6	0.36	0.60
S7	0.47	0.49
S10	0.59	0.47
S11	0.52	0.56
S12	0.49	0.46
S13	0.44	0.42
S14	0.49	0.51
S16	0.47	0.47
S17	0.45	0.52
MEAN error*	0.48	0.51
MEAN # epochs	104	104
N=13		

* compare with Figure 14

Note: # epochs – mean number of epochs used in automatic classification,
EMG detection rate is zero in both conditions per definition after the exclusion of trials with detected motor responses.

(c) Classification error in EEG – trials without visually detectable motor output

Subjects	ERROR_quasi	ERROR_imag
S1	0.21	0.12
S2	0.41	0.44
S4	0.05	0.22
S5	0.23	0.34
S6	0.03	0.05
S7	0.17	0.27
S10	0.17	0.33
S11	0.03	0.26
S12	0.00	0.08
S13	0.16	0.40
S14	0.16	0.15
S16	0.14	0.20
S17	0.15	0.16
MEAN error*	0.15	0.23
MEAN # epochs	78	92
N=13		

* compare with Figure 14

Note: # epochs – mean number of epochs used in automatic classification

Detailed repeated measures ANOVA results are available upon request (F.U.Hohlefeld@web.de).

Appendix E: Figures

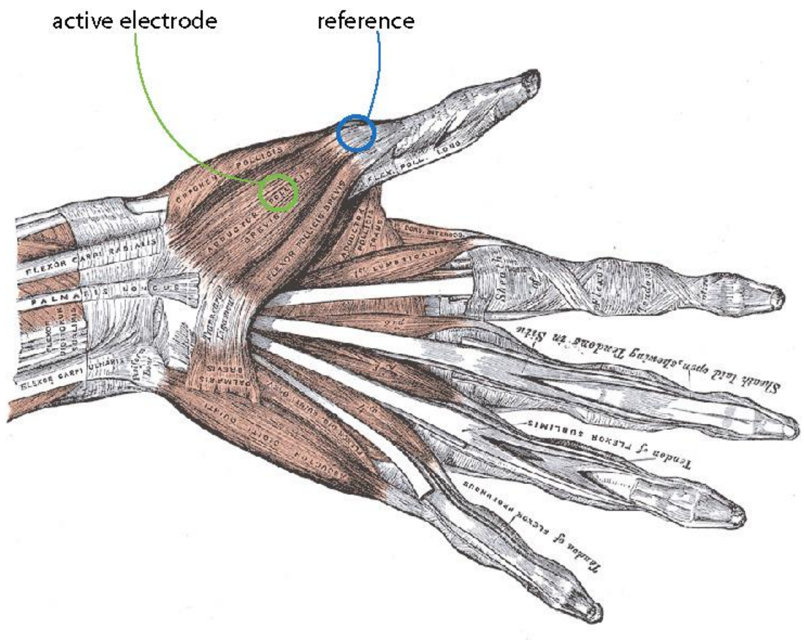


Figure A1. Abductor pollicis brevis and electrode montage.

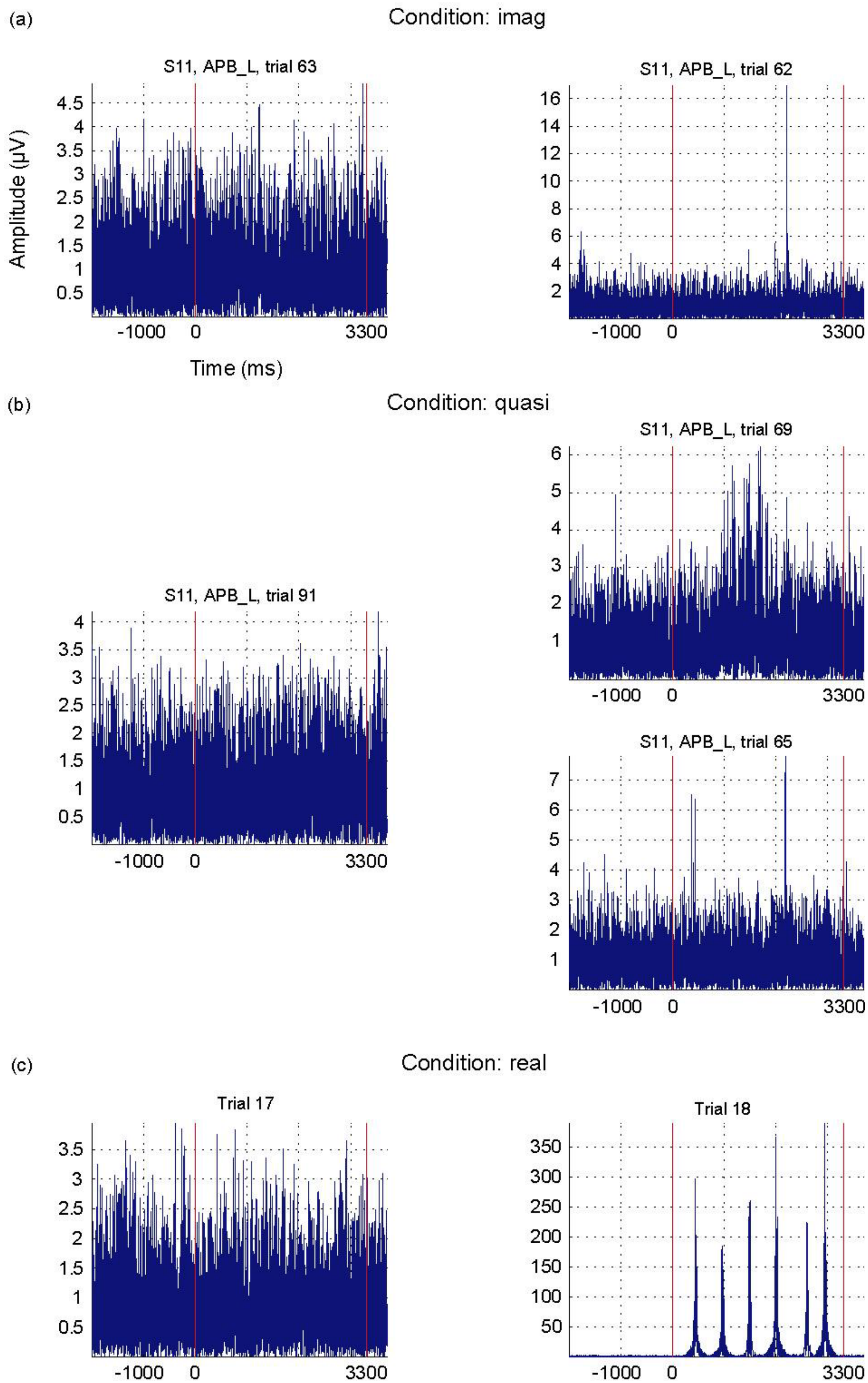


Figure A2. Single EMG trials from three different experimental conditions of a representative subject (S11). Imag – kinesthetic motor imagery, quasi – quasi-movements, real – movement execution, APB_L – abductor pollicis brevis left, red lines: 0–3300 ms; pre-stimulus interval: -1000–0 ms, post-stimulus interval: 70–3300 ms.

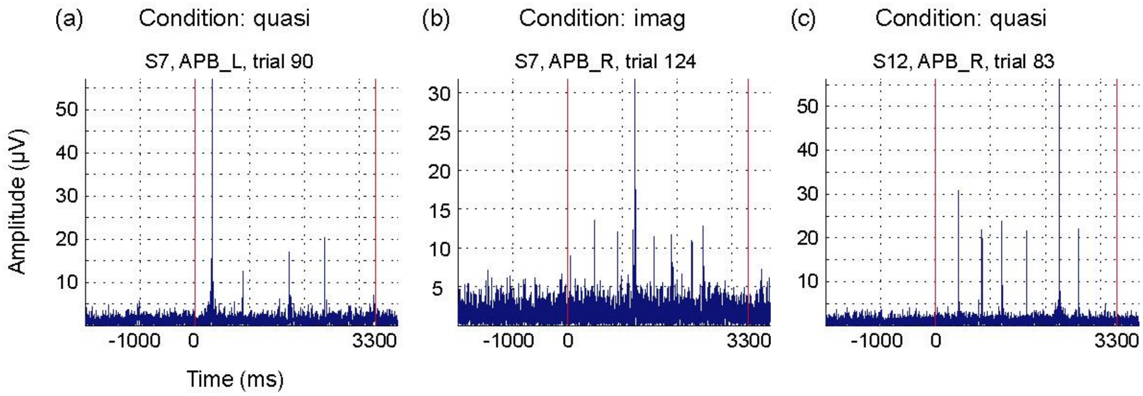


Figure A3. Single EMG trials from three different experimental conditions of two representative subjects (S7, S12).
Quasi – quasi-movements, imag – kinesthetic motor imagery, APB_R – abductor pollicis brevis right, APB_L – abductor pollicis brevis left, red lines: 0–3300 ms; pre-stimulus interval: -1000–0 ms, post-stimulus interval: 70–3300 ms.

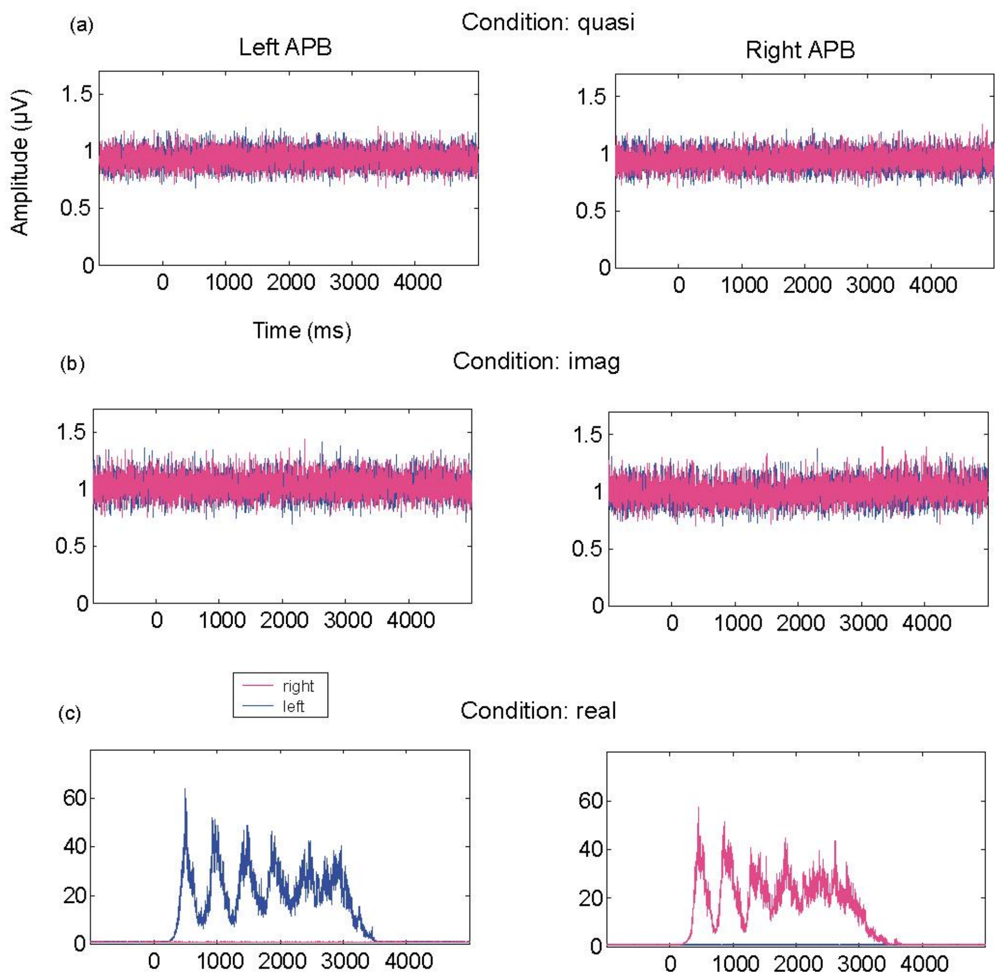


Figure A4. EMG averaged across trials for three experimental conditions of a representative subject (S11).
Quasi – quasi-movements, imag – kinesthetic motor imagery, real – movement execution,
APB – abductor pollicis brevis; pre-stimulus interval: -1000–0 ms, post-stimulus interval: 70–3300 ms.

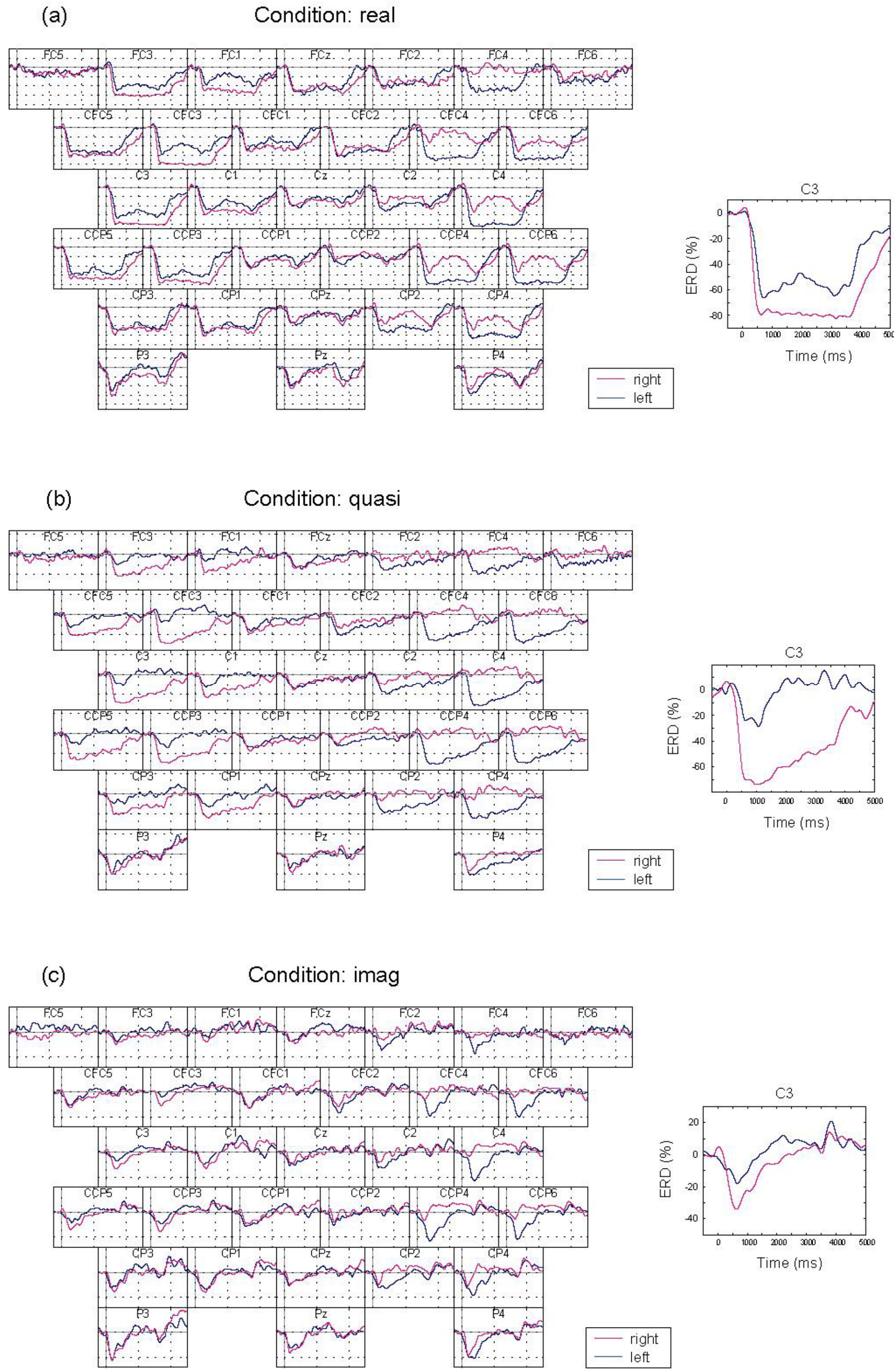
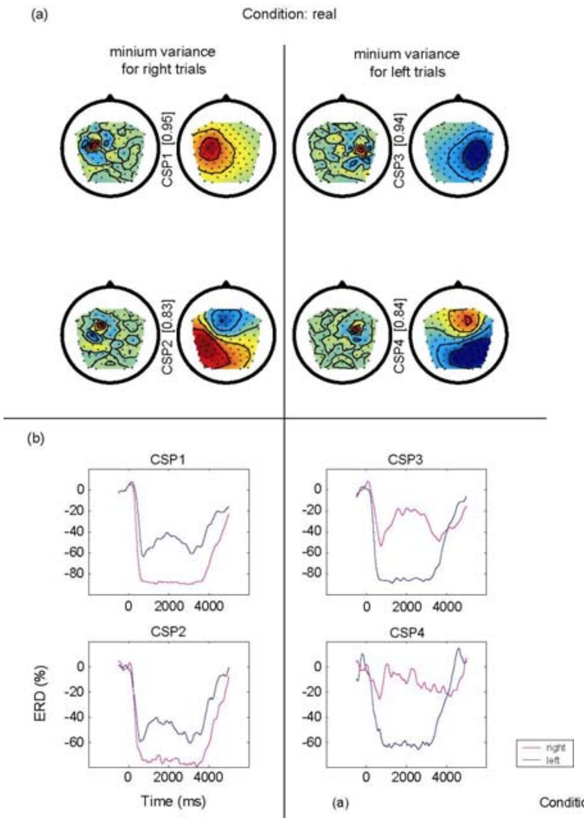
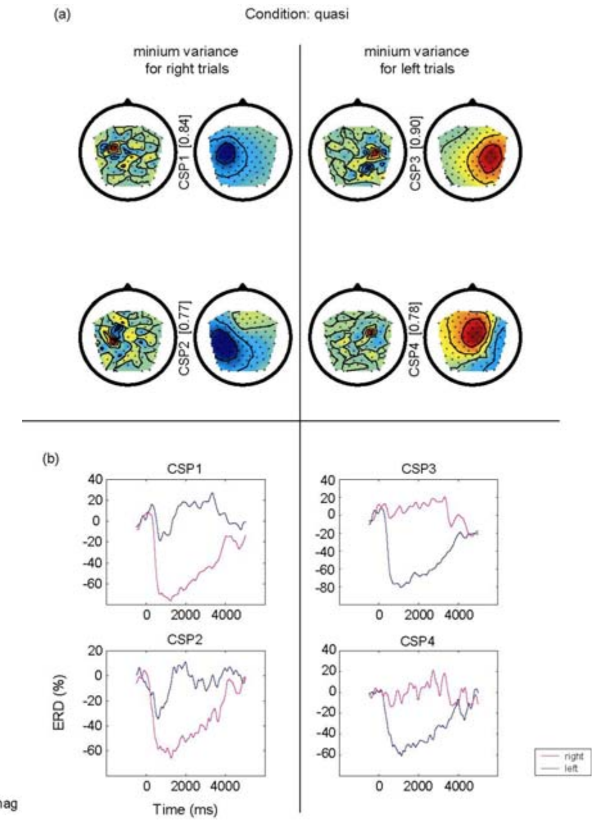
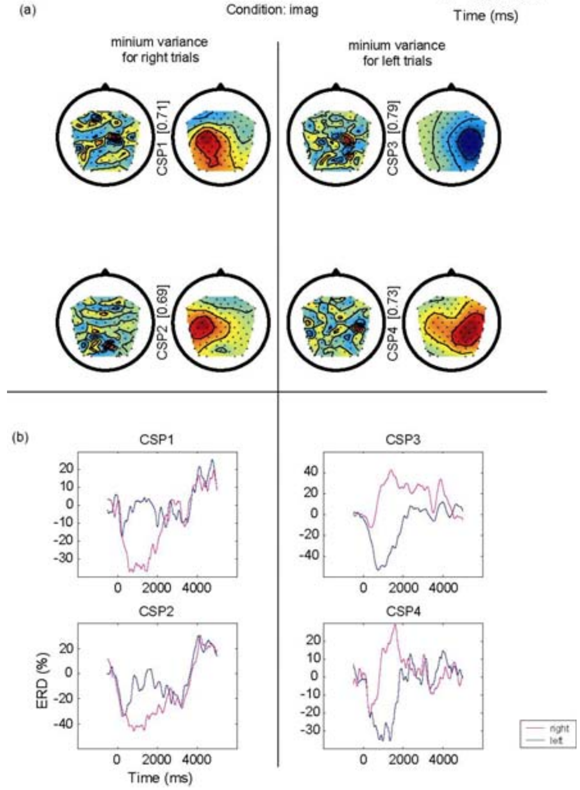


Figure A5. Laplacian ERD in three experimental conditions of a representative subject (S11).
ERD – event-related desynchronization, real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, right – right hand movement, left – left hand movement.
Calculation of ERD: ERD=(POST-PRE)/POST*100
POST=averaged electrophysiological activity in post-stimulus interval over channel with strongest ERD (70–3330 ms), PRE=averaged electrophysiological activity in pre-stimulus interval over channel with strongest ERD (-500–0 ms); negative values indicate attenuation of spontaneous oscillations in the frequency range of 8–13 Hz in most reactive channels over central sensorimotor regions, positive values indicate the enhancement of these rhythms.







Left: *Figure A6*, right: *Figure A7*, bottom: *Figure A8*. Common spatial patterns and ERD for three experimental conditions of a representative subject (S11).
CSP – common spatial pattern, ERD – event-related desynchronization, real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, right – right hand movement, left – left hand movement. POST=averaged electrophysiological activity in post-stimulus interval over channel with strongest ERD (70–3330 ms), PRE=averaged electrophysiological activity in pre-stimulus interval over channel with strongest ERD (-500–0 ms); negative values indicate the attenuation of spontaneous oscillations in the frequency range of 8–13 Hz, positive values indicate the enhancement of these rhythms.

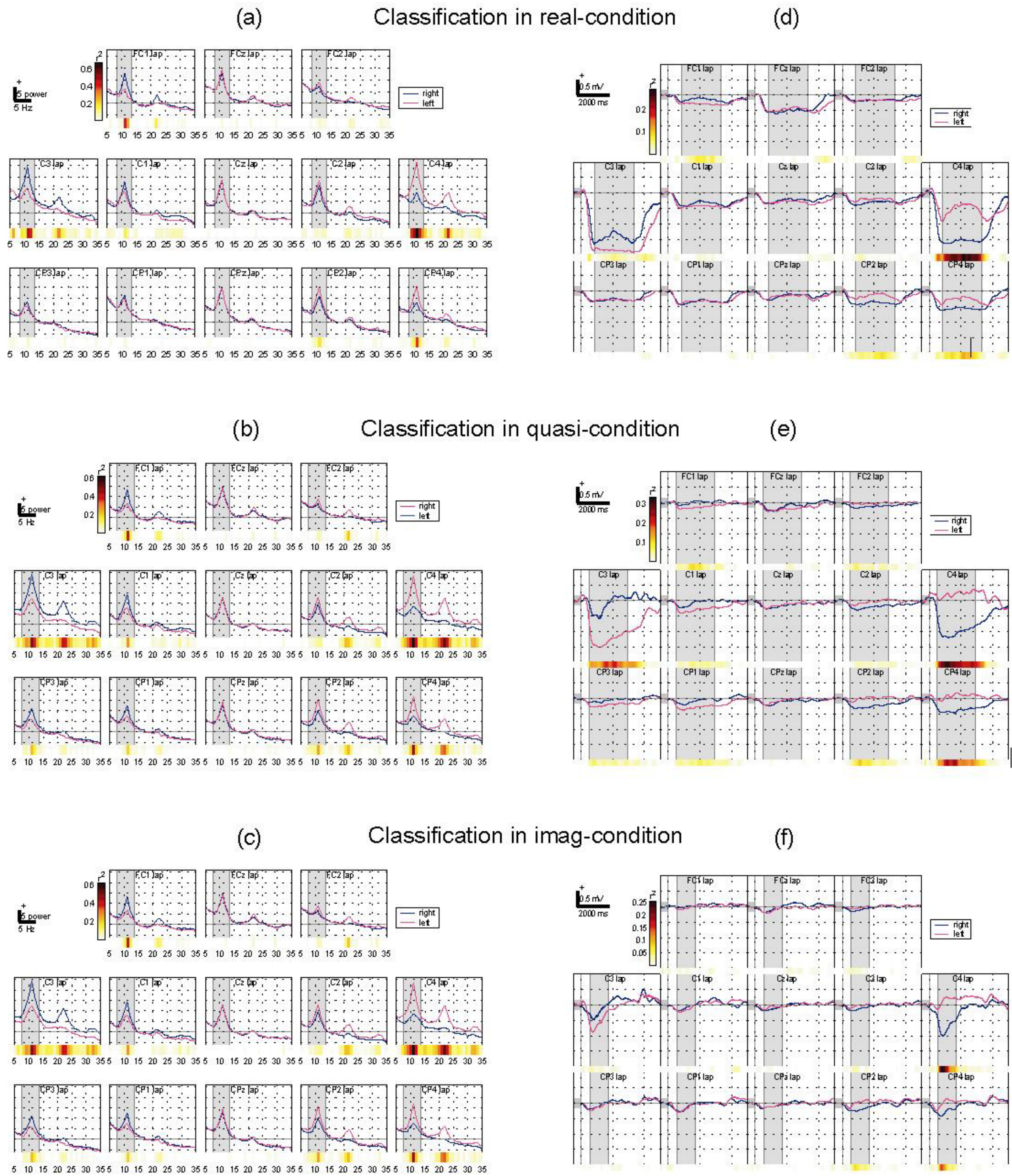


Figure A9. Single trial EEG classification in three experimental conditions for a representative subject (S11). A-c: Automatic selection of the optimal frequency band for discrimination between left and right movement class; d-f: Selection of the optimal post-stimulus interval for discrimination between left and right movement class on basis of event-related desynchronization. Real – movement execution, quasi – quasi-movements, imag – kinesthetic motor imagery, lap – Laplacian filtering, right – right hand movement, left – left hand movement.
