Imagined hand tapping:

A time-locked paradigm for Brain-Computer Interfaces

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ABSTRACT

Brain-Computer Interfaces (BCIs) can greatly improve the quality of life of 'locked-in' patients, since such a system controls an external device without muscle activity. In present day BCIs, EEG is predominantly used as a recording technique to register brain activity and the most widely used brain signals are sensorimotor rhythms, which can be modulated by imagining movements of hands, feet or tongue. One problem in developing a BCI is the need for prolonged training, which might be reduced by introducing a time-lock to the mental imagery. In the present study, participants imagined hand tapping time-locked to an auditory stimulus. We investigated whether this paradigm could work in a BCI. The experiment consisted of a training session, after which kernel logistic regression determined classification parameters. These were used in a test session, in which the participants received auditory feedback on their performance. In an actual movement pilot, one subject showed an alternating pattern of ERS and ERD in accordance to the alternation of rest and movement and performed with a classification rate of 87 % ($p < 0.0001$) on the training session. In the test session, the performances were 54 % (n.s.), 77 % ($p < 0.0001$), 80 % ($p < 0.0001$) and 74 % ($p < 0.0001$) over blocks. This subject did not show any significant classification rates on imagined movement, whereas another subject did, i.e. 58 % ($p = 0.0003$) in the training session. Two subjects did not show any significant results and were excluded from analysis. The current data do not convincingly show that time-locked imaginary hand tapping works as a paradigm for BCI. Future work should focus on selection of classes, selection of frequency bands, using spatial filters and optimizing the auditory feedback or switching to visual feedback.

INTRODUCTION

Patients suffering from neuromuscular diseases can have difficulties performing even the simplest actions. One example of such a disease is amyotrophic lateral sclerosis (ALS), which involves a steadily progressive degeneration of motor neurons leading to an inability of the brain to control movements. In the final stage of this disease, patients become totally paralyzed (or 'locked-in') and are hence not able to communicate. An external device such as a speller, a computer, a wheelchair or functional electrical stimulation (FES), which can be controlled without muscle activity, would greatly improve the quality of life of these patients. This is the domain of Brain – Computer Interfaces (BCIs). BCIs translate brain signals into output that communicates with the outside world. Since this new communication channel does not rely on peripheral nerves and muscles, it can be used by people with severe motor disabilities. With a BCI, patients will be able to express their thoughts and intentions to the outside world by controlling a device using only their brain (Leuthardt, Schalk, & Wolpaw, 2004; Wolpaw, Birbaumer, & McFarland, 2002).

The BCIs developed up until now can be classified into different categories based on a number of features. The first feature to distinguish different systems is invasiveness. Invasive BCIs use activity recorded by brain-implanted micro- or macroelectrodes measuring the activity of single neurons or the activity of multiple neurons in an ensemble. This type of recordings has a much higher spatial resolution, a better signal-to-noise ratio, and provide signals over a larger frequency range than non-invasive methods. However, BCIs depending on electrodes within the brain face substantial problems in achieving and maintaining stable long term recordings, since the tiny electrodes are susceptible to signal degradation due to encapsulation (Leuthardt et al., 2004). An intermediate BCI technology uses electrocorticographic activity (ECoG), which is recorded from the cortical surface. With this technique, the gain in long-term stability changes more profoundly than the loss in spatial resolution (Leuthardt et al., 2004). However, clinical studies using this method for BCI can generally only be conducted with epilepsy patients under highly constrained clinical conditions. In contrast, non-invasive techniques are more convenient, easier to study and safer. The methods employed for non-invasive BCIs to date include electroencephalography (EEG, e.g. Scherer et al., 2008; Wolpaw & McFarland, 2004), magnetoencephalography (MEG, e.g. Lal et al., 2005), functional Magnetic Resonance Imaging (fMRI, e.g. Hinterberger et al., 2004b; Weiskopf et al., 2003; Weiskopf et al., 2004; Weiskopf et al., 2005) and Near Infrared Spectroscopy (NIRS, e.g. Coyle, Ward, & Markham, 2004; Sitaram et al, 2006). EEG, which measures cortical potentials over the scalp, is the most widely used recording technique for BCI, since it has a higher temporal resolution than NIRS and fMRI (Gazzagina, Ivry, & Mangun, 2002, chap. 4). Furthermore, the equipment is portable and relatively inexpensive compared to MEG and fMRI. The present study will exclusively focus on EEG-based BCI.

The second feature upon which a distinction can be made between current BCI systems is the physiological signal they extract. Here, only electrophysiological signals will be discussed. The first class of brain patterns under investigation for use in BCI systems are steady-state evoked potentials (e.g. Hill, Lal, & Bierig, 2004; Müller-Putz, Scherer, & Neuper, 2006), such as the steady-state visual evoked potential (Solis-Escalante & Yañez-Suárez, 2006), the steady-state somatosensory evoked potential (SSSEP; Nangini, Ross, & Tam, 2006) and the auditory steady-state response (ASSR; Roß, Borgmann, & Draganova, 2000). A more frequently observed brain pattern for BCI is the P300 evoked potential (Farwell and Donchin, 1988), which is the positive peak in the EEG measured over the parietal cortex at about 300 ms after presentation of a 'rare' auditory, visual or somatosensory event. An advantage of the P300 – based BCI is that it does not need any initial user training. However, the P300 response attenuates with age. That is, the amplitude is reduced for older adults compared to young adults (Donchin, Miller, & Farwell, 1986). Birbaumer and colleagues (1999, 2000) focused on slow cortical potentials (SCPs) as a way to drive a BCI. It was shown that people can learn to control SCPs and thereby control movement of a cursor on a screen. A major drawback of this task for BCI purposes is that it needs a training period of several months, which might be burdensome for patients.

The most widely used brain signals for BCI are sensorimotor rhythms, which comprise μ (8 – 12 Hz) and central β (13 – 28 Hz) oscillations. Typically, imagination of movements involves these rhythms. In a movement imagery task, subjects are asked to imagine repetitive movements of hands, feet or tongue. Various studies have shown that imagining a movement results in similar EEG signatures as the preparation and execution of the actual movement (Green, Baily, & Sora, 1997; Neuper & Pfurtscheller, 2001; Pfurtscheller & Neuper, 1994; Pfurtscheller, Neuper, & Brunner, 2005). Specifically, two aspects of EEG activity are associated with imagined movement. One is a decrease in power in the sensorimotor rhythms about 2 seconds prior to movement onset. After termination of the movement, an increase in power in the same rhythms occurs. These phenomena are called event-related desynchronization (ERD) and event-related synchronization (ERS or beta rebound) respectively (Pfurtscheller & Lopes Da Silva, 1999).

Motor imagery, as described in the literature so far, can be subdivided into two different modes, namely the visual-motor mode and the kinesthetic mode of imagery (Neuper, Scherer, & Reiner, 2005). In the visual-motor mode, participants are instructed to visualize watching themselves or another person move. In contrast, participants are asked to imagine how it would actually feel to perform the movement themselves, i.e. first-person perspective, in the kinesthetic mode of imagery. Neuper and co-workers (2005) investigated the effects of imagining in these different modes on single-trial EEG. They observed that motor imagery strategies emphasizing either kinesthetic or visual-motor representations are associated with distinct ERD and ERS patterns with respect to spatial distribution and involved different frequency components. Consequently, only kinesthetic motor imagery, but not visual-motor imagery, resulted in detectable EEG changes.

Currently, several BCI systems based on motor imagery are being developed. Already in 1997, Pfurtscheller, Neuper, & Flotzinger reported that the imagination of right and left hand movement can be accurately discriminated by a classifier. Note, however, that adequate classification performance could only be achieved in subjects pre-selected based on the robustness of their ERD and ERS. They further developed this concept (Pfurtscheller, Brunner, & Schlögl, 2006a; Pfurtscheller et al., 2006b) and studied the use of motor imagery to control a virtual environment in which three able-bodied participants were asked to imagine foot movements (Scherer et al., 2008). It was recently shown that this system also performs successfully when used by a tetraplegic patient (Leeb et al., 2007). Another example of the use of sensorimotor rhythms is the BCI system developed by Wolpaw & McFarland (2004). In these experiments, both healthy volunteers and patients with spinal cord injury learned to control a cursor by means of motor imagery. Specifically, multidimensional cursor control was achieved by determining a weighted combination of the amplitudes in the μ (8 – 12 Hz) and β (18 – 28 Hz) frequency bands over the right and left sensorimotor cortices.

In the afore-mentioned studies using motor imagery, the subjects had to go through substantial training before adequate performance was acquired in controlling the output device. From a clinical point of view, this amount of training is too demanding for patients. Consequently, it is of great importance that the dependence on long-term training is reduced. Besides the need for prolonged training, the poorly understood problem of BCI illiteracy recently came into the focus of attention. Nijholt et al. (2008) estimated that about 20 percent of subjects do not show strong enough motor-related μ rhythm variations for the effective use of a BCI. Obviously, this obstacle prohibits home use of a BCI system for many patients. A final problem of current BCI systems is the great inter-subject and intra-subject variability (Wolpaw, 2007).

Blankertz et al. (2006, 2007) attempted to tackle these problems by ‘letting the machine learn’. This approach involved the use of advanced signal processing and machine learning techniques to cope with inter-subject variability and reach adequate performance without extensive training. Subjects began the experiment with a calibration measurement in which they were asked to imagine different kinds of hand and foot movement. Subsequently, the data were investigated by the experimenter to identify the two classes that gave best discrimination. These classes were used to train a binary classifier, yielding subject-specific parameters. In the following feedback session, subjects received feedback on their performance by classifying the imagined movements using the subject-specific parameters. Moreover, classifier parameters, i.e. bias and scaling, were adjusted on-line to achieve optimal performance.

In a previous off-line study in our lab, Geuze, Desain & Gielen (2007) tried to reduce the amount of training by introducing a time-lock to imagined movements. Three participants were instructed to imagine hand taps in a regular pattern in which rest and movement periods were alternated rhythmically based on an auditory stimulus. It was expected that ERD and ERS were alternated in accordance with the period in the pattern, i.e. an ERD in the movement period and an ERS in the rest period. The investigators proposed that the rhythmical pattern in the EEG signal would greatly improve the performance of the classification algorithms. The results indeed revealed the rhythmical pattern of alternating ERD and ERS in the μ and low β frequency bands of the EEG signal in actual movement. Imaginary movement showed the same deflections in the signal, though less pronounced. However, the classification results were rather poor. The best observed performance for actual movement was 65 % and for imaginary movement 68 %. When including multiple trials in analysis, the classification rate improved profoundly.

The present study was designed to transform this off-line study into an on-line BCI setup. Consequently, the main question was whether time-locked hand tapping could work as a paradigm in an on-line BCI setting. To address this issue, an experiment was set up which consisted of a training session directly followed by a test session. During the training session, subjects were asked to perform and imagine hand movements, which were time-locked to an auditory stimulus, resulting in an alternating pattern of rest and movement. To improve classification performance with respect to the previous experiment (Geuze et al., 2007), the movement times were decreased, since brisk movements tend to elicit a larger desynchronization in the μ rhythm (Stancák & Pfurtscheller, 1997). Furthermore, subjects were specifically instructed to imagine the movement as if they were performing it themselves in order to make sure that they used the kinesthetic mode of motor imagery. Data collected in the training session were utilized to train the classification algorithm, yielding subject-specific parameters, which were used in the test session to classify each hand tap. Using data of the previously mentioned off-line study (Geuze et al., 2007), we looked for a classification algorithm performing better than the described algorithms in that work. The best performing classification algorithm was found to be based on kernel logistic regression (Bishop 2008, chap.4; Bishop 2008, chap 6; Minka, 2005) and was used in the present study.

During the test session of the current experiment, participants received feedback on the classification results of each hand tap. The auditory modality was used for this purpose, since visual feedback might have introduced eye movements disturbing the classification of the ongoing EEG signal. Moreover, Hinterberger and co-workers (2004a) argued that patients in advanced stages of ALS no longer have the ability to focus gaze sufficiently. Consequently, the authors compared learning to regulate SCPs using auditory and visual feedback. The study revealed that adequate BCI control could be achieved with auditory feedback. Nijboer et al. (2008) investigated the feasibility of auditory feedback in a BCI using sensorimotor rhythms. Sixteen participants learned to control their SMR. Feedback was realized by either harp sounds for ERS or bongo sounds for ERD. The authors reported that auditory feedback led to approximately the same level of performance at the end of the experiment as visual feedback.

METHODS

Design

In the present study, participants were asked to imagine hand movements. As illustrated in Figure 1, the experiment consisted of a training session directly followed by a test session. During the training session, no feedback was given to the subjects. The data of the imagined movement task collected during this session were fed into the classification algorithm. The parameters of the trained classifier were then utilized in the test session of the experiment to classify each hand tap. The classification decision for either left or right hand movement was directly fed back to the subject by means of auditory feedback.

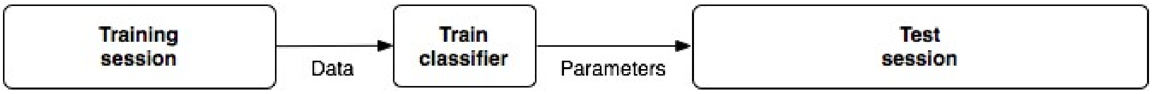

Figure 1. Experimental design. Data collected in the training session were fed into the classifier, yielding parameters, which were utilized in the test session to classify the individual hand taps. The classification decision was directly fed back to the subject by means of auditory feedback.

Stimuli

Audio. An auditory stimulus was used to time the hand movements. One movement cycle consisted of a 500 ms resting period and a 500 ms movement period. During the resting period, the auditory stimulus was a continuous sound with a frequency of 300 Hz. Subsequently, the frequency of the sound smoothly increased to 400 Hz over 333 ms during which the subjects were asked to raise their hand. In the last part of the 500 ms movement period, i.e. a 167 second period, the frequency of the sound smoothly decreased to the base frequency of 300 Hz. During this time, the subjects put their hand back on the table. The frequency modulated sound is shown in Figure 2A. At the moment the hand was required to land, a 20 ms tick on a woodblock was presented. The frequency modulated sound as well as the tick was repeated for every hand tap. The auditory stimulus was presented with loudspeakers.

Video. To instruct the participants which hand movement to imagine, a short video was presented showing a hand tap of either the right or left hand. During the taps, the auditory stimulus was presented as well. The hands in this video were recorded from a first person perspective. One frame of the video of left hand movement is shown in Figure 2B.

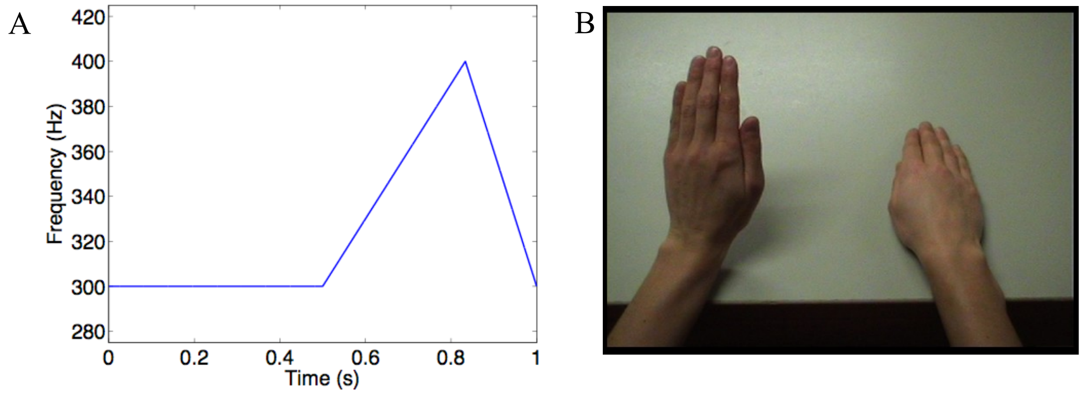

Figure 2. A: Frequency modulation of the ongoing sound. The frequency rises from 300 to 400 Hz from 0.5 to 0.83 seconds of the movement cycle and then decreases to 300 Hz during the last part of the movement cycle. B: Example frame of the video of left hand movement.

Procedure

Participants were seated in a comfortable chair looking at a 17-inch TFT monitor placed on the table in front of them, on which the stimuli were presented. They were asked to place their hands on the table. During the experiment, the subjects' hands were hidden from sight in order to encourage the subjects to use the kinesthetic strategy of imagination. The participants could press a foot pedal to continue to the next trial. In this way, they were able to determine the pace of the experiment and move or blink their eyes between the trials.

Training session. During the training session of the experiment, data was collected for training of the classification algorithm. This session consisted of three blocks each subdivided into twelve trials. In each block, six trials for right hand movement and six trials for left hand movement were randomly interleaved. The participants were required to both execute and imagine a hand movement in each trial. A trial started with a six second baseline period (see Figure 3A). During the first half of the baseline period, i.e. baseline 1, there was no sound. After these three seconds, the sound started and continued throughout the whole trial. Consequently, the second part of the baseline period, i.e. baseline 2, included sound. The subjects were required to look at a white fixation cross during the baseline period. Then, the white fixation cross disappeared and a video with two taps, i.e. 2 seconds, of either the right or left hand was shown to instruct the participants which hand to move. If a right hand was moving in this video, the subjects were supposed to move and imagine right hand movement in the rest of the trial, and vice versa. Next, the white fixation cross appeared again and the subjects were required to execute the movement for five seconds, i.e. five hand taps. Finally, the white fixation cross changed into red, which was a cue for the subjects to stop executing and start imagining the hand movement. The subject was required to imagine twelve hand taps.

Test session. During the test session of the experiment, every single hand tap was classified and the result was directly fed back to the subjects. There were five blocks, each with twelve trials. Every block was subdivided into six right hand trials and six left hand trials. In these trials, the participants were asked only to perform imagined hand movements. As in the trials in the training session, a trial started with a six second baseline period of which three seconds without and three seconds with sound. Next, a video with two hand taps was presented as instruction. Finally, a red fixation cross appeared, which served as a cue for the subjects to start imagining the movement shown in the video. They were required to do so for seventeen seconds, i.e. seventeen hand taps. A graphical representation of a typical trial in the test session is shown in Figure 3B.

A

B

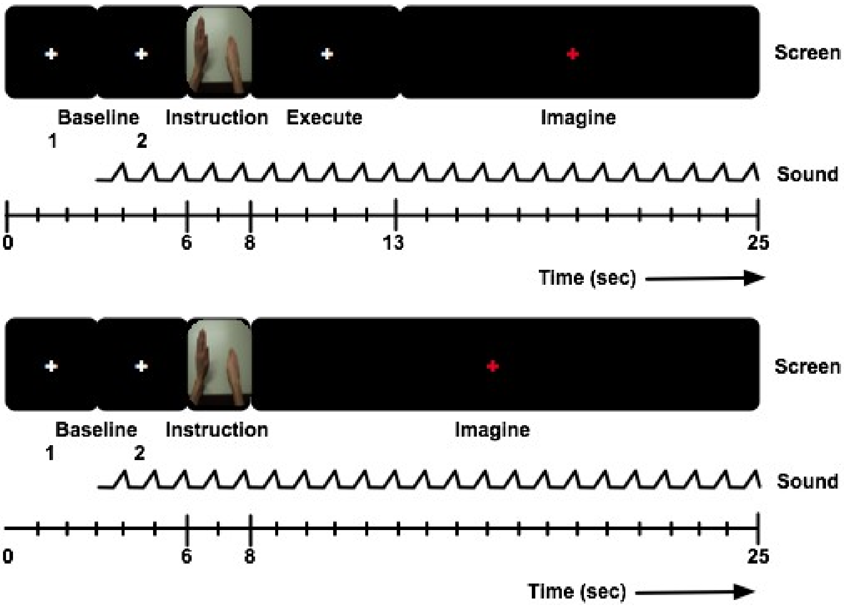

Figure 3. A: Trial in the training session of the experiment. The first six seconds constituted a baseline period of which three seconds are without the ongoing sound (baseline 1) and three seconds with (baseline 2). The ongoing frequency modulated sound is shown in the middle trace of the figure. After the baseline period, the white fixation cross disappeared and two hand taps were presented, which instructed the subjects which hand to move during the rest of the trial. This was followed by a reappearance of the white fixation cross, indicating that the subject was to perform the movement shown in the video for five seconds. After a change in colour of the fixation cross, the participants were required to imagine the hand movement for twelve seconds. B: Trial in the test session of the experiment. It starts with the six second baseline period. After the instruction video, the subject imagined the movement for seventeen seconds.

Auditory feedback

During the test session, the participants received auditory feedback on their performance. The feedback consisted of changing the location of the 'tick' sound, which indicated when the subjects were supposed to let their hand fall back on the table. When the classifier classified the hand tap as a right hand movement, the tick was presented at the loudspeaker at the right side of the subject. If a tap was classified as a left hand tap, the tick moved to the loudspeaker at left side of the subject. Depending on how large the probability for a certain class was, the tick was presented more or less to the associated side of the subject. For example, if the probability for a right hand tap was very high, the tick was only presented on the right loudspeakers. However, if the probability was very low, the tick was presented on both the left and right loudspeakers in a way that the subject perceived it to be only slightly on his or her right.

Since single trial classification is rather difficult, the probabilities vary greatly from trial to trial. To make sure that the participant was adequately informed by the feedback, we did not want the tick to fluctuate as quickly as the probabilities do. Consequently, the location of the tick was calculated not only based on the probability of the current tap, but also on the probabilities of all previous taps in the trial. Specifically, the location linearly derived from a weighted sum of the probabilities of the previous taps in the trial. The weighted sum was computed a recursive function,

$$P_t = \frac{0.8 \cdot P_{t-1} + C_t}{Z} \qquad (1)$$

in which t represents the current tap, P_t the weighted sum of all classification probabilities up to tap t, i.e. the current output, C_t the current classification probability and Z a normalization factor, which scales P_t between 0 and 1. The factor 0.8 was chosen based on subjective experiences of the subjects in pilot experiments. Using this factor, the half-life of the function was 5 hand taps.

Pilot experiment

To test the experimental procedures and auditory feedback, a pilot experiment was performed prior to the experiments described above with one of the subjects. In this pilot, the task only contained actual movement and no imaginary movement. The training session consisted of two blocks, whereas the test session was four blocks. The trials were the same as described above, except for the fact that the fixation cross remained white throughout the trial. In other words, the subject was instructed to perform the movement throughout the trial.

Equipment

All stimuli were generated as MIDI in Matlab 7.2 and presented with Logic Express 7.2.3, which is a MIDI sequencer. EEG was recorded using 256 sintered AG/AgCl active electrodes. The signals were amplified using a Biosemi ActiveTwo AD-box and sampled at 2048 Hz. The recordings took place in a sound proof and electrically shielded room in order to minimalise environmental noise in the EEG signals. Eye movements and blinks were monitored by two electrodes. One was placed above the right eye slightly to the lateral side and the other one slightly lateral below the left eye. Furthermore, hand movements were monitored by measuring electromyographic (EMG) activity during the experiment, since some studies reported increased EMG activity during imagination of movements compared to resting periods (Jeannerod, 1995). Specifically, surface EMG was recorded from the main wrist extensors of the right and left arm.

Subjects

Two female and two male right-handed volunteers participated in this study (age 24 - 31 years). They had little or no previous experience with this type of experiment. The subjects did not have any neurological disorders and had normal or corrected to normal vision and hearing.

Data analysis

Data analysis was done using Matlab and the FieldTrip open source Matlab toolbox that was developed at the F.C. Donders Centre for Neuroimaging (http://www.ru.nl/ fcdonders/fieldtrip).

Preprocessing. The EEG signals were preprocessed in several steps. First, the data was temporally downsampled from 2048 Hz to 128 Hz. Subsequently, the EEG signals recorded during the hand movements were extracted by slicing them into epochs of two seconds. Every epoch contained one movement cycle, i.e 500 ms rest and 500 ms movement, in the middle. Specifically, the epoch started 500 ms before rest onset and ended 500 ms after movement offset, yielding 500 ms overlap with both the previous and the next epoch. After slicing, the data was re-referenced using an average reference over all channels. Then, bad channels were automatically detected and removed based on prefixed thresholds for offset, 50 Hz line noise and offset jitter. Thresholds were 45 mV, 5e-4 mV^2 (with a bin width from 45 to 55 Hz) and 0.15 mV, respectively. The remaining channels were spatially downsampled to a standard 64 channel layout according to the 10-20 system, using spherical splines interpolation (Perrin, Pernier, & Bertrand, 1989). Finally, the downsampled data was highpass filtered with a cutoff frequency of 2 Hz, filtered for line noise at the frequency of 50 Hz and the trend was removed.

Time – frequency representation. A time-frequency representation, i.e. a power spectrum for each time point, was calculated using a fixed Hanning window of 500 ms (Challis & Kitney, 1991). Every epoch yielded a time-frequency representation of one movement cycle, i.e. 1

second, whereas the rest of the data was used for padding. Moreover, only the frequencies between 5 and 40 Hz were used in the analysis. Consequently, each epoch consisted of 21 time points (from 0 to 1 sec with steps of 0.05 sec) and 18 frequency bins (from 5 to 40 Hz with steps of 2 Hz).

Classification. The classification algorithm was based on linear logistic regression, which is a conditional statistical model of binary variable *y* given feature vector *x*. The probability that *y* belongs to the positive class given *x*, i.e. $P(C_+ | x)$, is given by the logistic sigmoid function,

$$P(C_+ \mid x) = y(x) = \frac{1}{1 + e^{(-w^T x)}} \qquad (2)$$

which acts on the inner product of *x* with vector *w*. This linear combination defines the hyperplane separating the data of each class from each other. Maximum likelihood estimation (MLE) was used to determine the model parameter. In other words, MLE sets *w* to the value that maximizes the likelihood function. This algebraic problem can be solved by minimizing the negative log of the likelihood function, which is called the error function (Bishop 2008, chap.4; Minka, 2005). To avoid over fitting of the model, a quadratic regularization parameter was added to the error function. Essentially, this regularization term penalizes large weights and allows small weights to influence the model, implying that small changes in the features are considered as less important and large changes as important. The value of the regularization parameter was determined using 10-fold cross-validation. Furthermore, the logistic regression model was implemented with a linear kernel (Bishop 2008, chap.6) in order to increase computational accuracy.

RESULTS

Of the four subjects we measured in this experiment, two subjects did not show any significant classification results. Consequently, their results will not be discussed here. Subject 1 performed both the pilot experiment with actual movement and the experiment with imaginary movement. However, she only showed significant classification results on actual movement. Subject 2 showed significant results on both actual and imaginary movement, though the classification rate on imaginary movement was poor. Hence, the results presented here will mainly focus on actual movement. The results for imaginary movement of Subject 2 are briefly discussed at the end of this section.

Neurophysiology

The data of the training session without feedback were used to describe the time-frequency representation (TFR) of the ERD and ERS. Since Subject 1 showed the strongest motor-related modulations in the ongoing EEG, the time-frequency representations of only this subject are shown for illustration. The figures are based on the pilot with actual movements.

Figure 4 shows the activity pattern of left and right actual movement of channels C3 and C4, which are situated roughly over the left and right hand area of the motor cortex, respectively. Although motor-related modulations in the EEG signal were observed over both the central and parietal areas, C3 and C4 revealed the largest fluctuations in power as a result of the hand movements (see Figure 8 and 9 in the Appendix). They reveal an alternating pattern of ERS during the rest period of the cycle, i.e. from 0 – 0.5 seconds, and ERD during the movement period, i.e. 0.5 – 1 second. Note, however, that the pattern is delayed with respect to rest and movement onset. Specifically, at rest onset, i.e. at 0 s, there is still an obvious decrease in power, which continues until halfway the rest period. Similarly, the ERS continues after movement onset at 0.5 s. Furthermore, a clear lateralization for right hand movement can be observed. In other words, the power fluctuations are more pronounced over the contralateral hemisphere than over the ipsilateral hemisphere. For left hand movement, the lateralization was less obvious. Specifically, the difference between power in left and right hemisphere is larger for right hand than for left hand movements. Finally, the largest modulations in ongoing EEG activity involve frequencies between 16 and 26 Hz, which is typically in the range of the central β rhythm (18 – 28 Hz). The μ rhythm (8 – 12 Hz) shows the same temporal modulation though less strong.

Subject 2 showed the same patterns, though less clear. This is partly due to the fact that this subject did not perform the pilot and hence less data on actual movement were collected. The neurophysiological results of Subject 2 (data not shown) revealed an ERS during the rest period at slightly higher frequencies than Subject 1, namely between 23 and 31 Hz. Interestingly, we also observed a power decrease between 7 and 13 Hz during the rest period, whereas we only expected a decrease in power to occur in the movement period and an increase during the rest period, as described in literature (Pfurtscheller & Lopes Da Silva, 1999). Furthermore, the movements were less lateralized than in Subject 1 and the spatial distribution of activity showed that the largest power fluctuations were situated mainly at the central electrodes, i.e. C1, C2, Cz, CP1, CP2 and CPz.

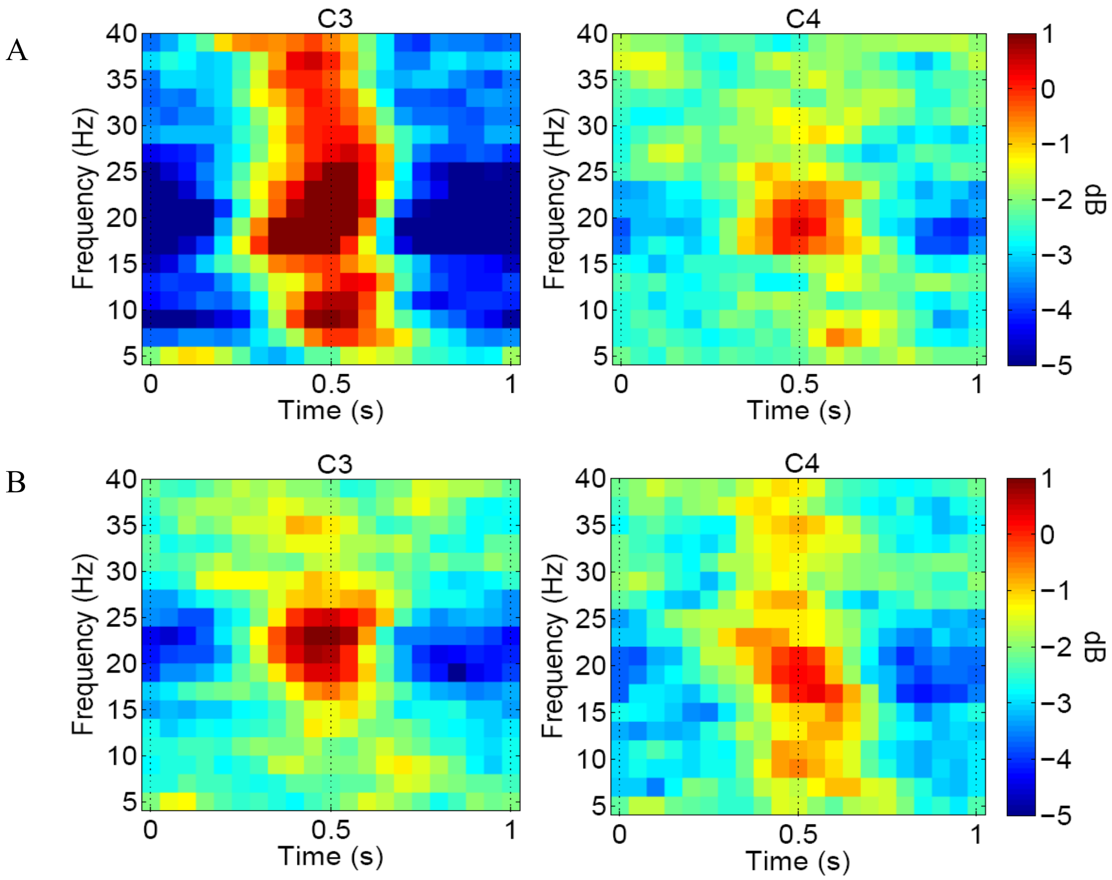

Figure 4. Time-frequency representation (TFR) of right hand movement (A) and left hand movement (B) of Subject 1. Power fluctuations measured over C3 (left panel) and C4 (right panel) are shown. The x-axis denotes time (s) in which one movement cycle is plotted, i.e. 0 - 0.5 s is the rest period and 0.5 - 1 s is the movement period. The dotted line indicates the transition between the two phases of the cycle. The y-axis denotes frequencies from 5 to 40 Hz. The power is scaled from -5 to 1 dB with the color map.

To obtain more insight in the spatial, spectral and temporal distribution of the ERD and ERS, a so-called Canonical (CANDECOMP) or Parallel Factors (PARAFAC) decomposition was calculated for the time-frequency representation of the power of Subject 1 (Harshman & Lundy, 1994). Essentially, this approach weights the spatial, spectral and temporal contribution at each sample such that the product of the three contributions yields the total power in that sample. It was computed using an alternating least-squares method. The decomposition has previously been applied with success on EEG time-frequency data (De Vos et al., 2007). After calculating the TFR of each condition, the right hand movement data were subtracted from the left hand movement data. Then, the decomposition was applied (see Figure 5). The spatial distribution in Figure 5A shows that the differences between left and right movement are not only situated over the motor areas, but also over the parietal areas. In Figure 4, a rough estimate could be made on the frequency distribution of the effect. In contrast, Figure 5B points out exactly that the movements mainly affect the frequencies between 15 and 23 Hz. Moreover, the power fluctuations in the μ rhythm are very small compared to the fluctuations in the central β rhythm. Interestingly, one can also see frequency modulations at high β (27 – 35 Hz) frequencies, which are approximately of the same size as the μ modulations. Finally, as shown in Figure 4, Figure 5C demonstrates the alternating pattern of in- and decreasing power over the movement cycle, in which the response of the power is delayed with respect to the phase in the movement cycle.

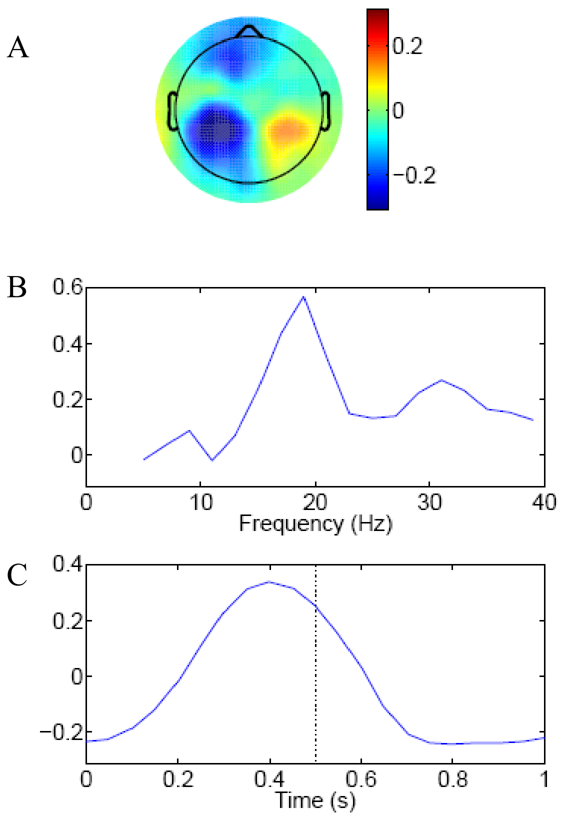

Figure 5. Decomposition of TFR data of the difference between left and right hand movement of Subject 1. This computation results in spatial (A), spectral (B) and temporal (C) contributions to the total power. Frequency is scaled between 5 and 40 Hz; time between 0 and 1 s in which the dotted line at t=0.5 s indicates the transition between rest period and movement period.

Classification

The data of the training session described in the previous section were used to train the classifier, which was based on kernel logistic regression. Both the rest period and the subsequent movement period were taken into account in classification. The classification rate of Subject 1 was 87 % ($p < 0.0001$), whereas the classification rate of Subject 2 was 60 % ($p = 0.003$). Note, however, that the result of Subject 2 was based on less data. To pinpoint which features of the data are important for the classifier to discriminate between the two classes, the weight vector as determined by the classifier was plotted (see Figure 10 in the Appendix). The weight vector shows the same characteristics as the spatial distribution of the TFR data: the largest weights are observed for electrodes C3 and C4. The parietal electrodes show large weights as well. Due to differences in lateralization between left and right hand movement, the classifier allocates more weight to the mentioned electrodes in the left hemisphere than those in the right hemisphere. The weight vector was decomposed (see Figure 6) to gain more insight in the spatial, spectral and temporal properties of the discriminative features.

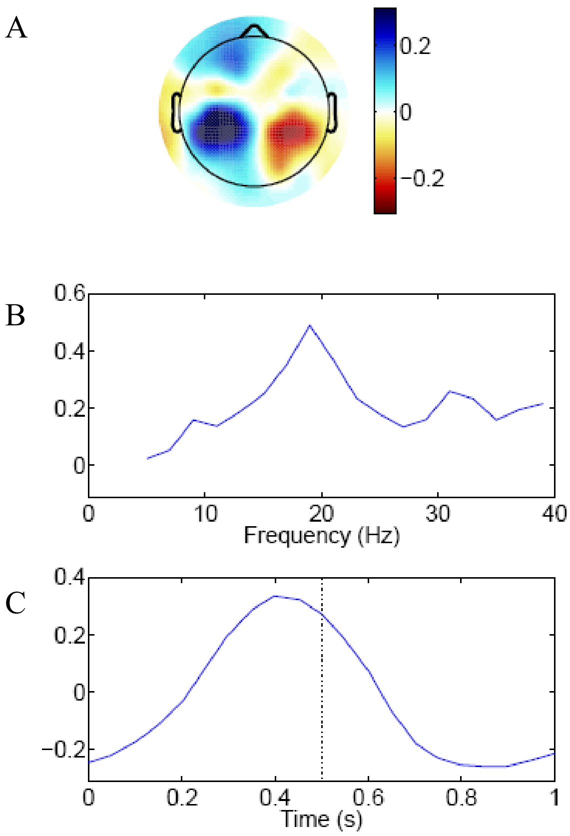

Figure 6. Decomposition of the weight vector determined by kernel logistic regression. This computation results in spatial (A), spectral (B) and temporal (C) contributions to weights. Frequency is scaled between 5 and 40 Hz; time between 0 and 1 s in which the dotted line indicates the transition between rest period and movement period.

The spatial distribution of the weights in Figure 6A shows that the main contribution to classification is from the regions over the motor and parietal cortices. Specifically, the classifier seems to have used the difference between the two hemispheres in discriminating between the two classes, since the blob over the left hemisphere contains negative weights, whereas the blob over the right hemisphere contains positive weights. Note also that the spatial distribution has the same properties as the difference TFR data between left and right hand movement. The same can be observed for the frequency distribution of the weight vector. The three peaks, which were present in the difference between left and right hand movement, also show up in this plot. Finally, the time distribution curve of the weight vector is similar to the time distribution of the difference between left and right hand movement. These results indicate that the classifier is able to find the largest differences between the two classes and to mark these features as important in discriminating between the two classes.

Feedback

Feedback was given to the subjects on their performance during the test session. To check whether the auditory feedback facilitates learning to control the sensorimotor rhythm, the performance over blocks of Subject 1 during the pilot experiment was assessed. The classification rates of the training session and the different blocks in the test session are outlined in Figure 7.

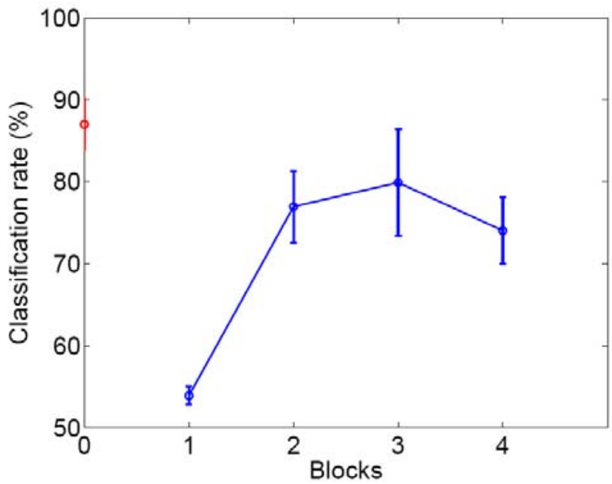

Figure 7. Classification rate over blocks. Block 0 consists of all the data of the training session. The subsequent blocks, i.e. block 1-4, are part of the test session. The classification rate of block 1 was not significantly different from pure chance. The rates of the other blocks were all significant with $p < 0.0001$. The error bars show 95 % confidence intervals, which were calculated based on the classification variability from trial to trial in each block.

The classification rate of the training session was 87 % ($p < 0.0001$), which is indicated as block 0. This value was obtained using 10-fold cross-validation on the training session data. Blocks 1 – 4 were part of the test session. The first block of the test session showed a significant decrease in performance as compared to the training session. The classification rate on this test set was approximately 54 %, which was not significantly different from pure chance. Over block 2 and 3, an increase to a level of 80 % was observed, i.e. approximately 77 % ($p < 0.0001$) in block 2 and 80 % ($p < 0.0001$) in block 3. Interestingly, these classification rates are not significantly different from the 87 % of the training session, indicating that feedback does not improve the performance of the subject compared to the non-feedback session. In block 4, the performance decreased slightly to 74 % ($p < 0.0001$), but this decrease was not significant.

Imagined movement

Only Subject 2 showed a significant classification rate on the training session with imagined movement, namely 58 % ($p = 0.0003$). However, this performance was considered to be too poor to evaluate the effects of feedback during the test session. Thus, the results on the test session will not be discussed here.

The spatial distribution (see Figure 11 and 12 in the Appendix) showed a similar activity pattern as actual movement in this subject. An ERS occurred during the rest period and an ERD during the movement period. The largest power modulations could primarily be found over the central electrodes. Neither for left hand imagery nor for right hand imagery a clear lateralization could be found. The power modulations were more pronounced for left hand than for right hand imagery, and the largest fluctuations occurred between 24 and 33 Hz.

DISCUSSION

In the present study, we investigated whether time-locked imagination of hand tapping works as a paradigm for BCI. The experiment started with a training session, of which the data were used for determining subject-specific parameters for classification. During the training session, subjects were asked to perform and imagine hand movements, which were time-locked to an auditory stimulus, resulting in an alternating pattern of rest and movement. In agreement with the previous off-line study in our lab (Geuze et al., 2007), we expected to find an alternating pattern of ERD and ERS in the μ frequency band. The training session was followed by a test session, in which every hand tap was classified and participants received auditory feedback on their performance. The feedback consisted of changing the location of the 'tick', at which the subjects were supposed to let their hand land on the table.

In 2 subjects, unfortunately, the classification algorithm did not find any features that enabled a reliable discrimination between left and right hand movement imagery. These data were excluded from our analysis. However, for improving the reliability of our BCI system, it is important to pinpoint why the imagined movement BCI failed in these two subjects. After investigation of the time-frequency representation, there was no detectable sensorimotor rhythm. The instruction to imagine the hand movements might have played a critical role in this context, since the subject's compliance with the instruction could not be assured. Consequently, they might have used an unfavourable mental strategy instead of the kinesthetic mode to imagine the movements (Neuper et al., 2005). To further investigate this idea, we performed an off-line analysis of the data gathered on actual movement during the training session. When the actual movement data contains a clear sensorimotor rhythm, one can be suspicious about the mental strategy used for the imagery part. In our case, however, the results of actual movement did not show any sensorimotor rhythms, let alone rhythmic modulations in accordance with the rest and movement alternation. This observation disproves the proposal that the participants used an unfavourable mode of imagery. Alternatively, Nijholt et al. (2008) argued that EEG might not be able to read motor imagery related activity in some subjects, because the cortical region involved is located tangential to the scalp. Hence, ERD and ERS are unsuitable measures for building a SMR-based BCI system for these subjects. This could explain the null results in our two subjects.

The issue of how to instruct the participants in such a way that they use the kinesthetic mode of imagery might have played a role in Subject 1. She performed very well in the actual movement pilot, i.e. a classification rate of 87 % on the training session and up to 80 % on the test session. However, the data on imagined hand tapping did not show any visible sensorimotor rhythm, suggesting that she did not use the kinesthetic mode of motor imagery. In actual movements, the ERD and ERS were clearly visible as reported by other researchers (Pfurtscheller & Lopes Da Silva, 1999; Pfurtscheller & Neuper, 1994). In addition, the ERD and ERS alternated with the phase of the movement cycle. In other words, an ERD occurred when the subject moved her hands and an ERS occurred in rest. This finding confirms the results of the previous off-line experiment (Geuze et al., 2007). The main focus of the motor-related activity was measured over the motor cortex. However, the parietal cortices also showed pronounced power modulations. These areas are believed to be involved in movement intentions, e.g. sensori-motor integration and planning of movements (Andersen and Buneo, 2002). Surprisingly, the largest power fluctuations in the ongoing EEG occurred in the central β frequency band, whereas it was expected to be in the μ rhythm (Pfurtscheller & Lopes Da Silva, 1999), and the ERS and ERD were delayed with respect to the movement cycle. These deviations from the findings of other studies are probably due to inter-subject variability. As reported before (Kim et al., 1993; Singh et al., 1998), the data also showed a clear lateralization for right hand movement, while the difference in power between the hemispheres was smaller for left hand movement.

During the test session of the pilot experiment, which only consisted of actual movements, Subject 1 received auditory feedback on the classification performance of every single hand tap. Specifically, the feedback consisted of changing the location of the 'tick' sound, which indicated when she was supposed to let her hand fall back on the table. By investigating the performance of the participant over blocks in the test session compared to the performance in the non-feedback condition, i.e. the training session, we verified whether the feedback facilitated learning to control the sensorimotor rhythm. The classification rate in the training session of the experiment was 87 %, which was obtained using 10-fold cross-validation on the training session data. The maximum classification rate of the four blocks in the test session was approximately 80 %, indicating that no improvement occurred with feedback. This unexpected finding raises the question why the subject did not improve her performance on the BCI during the test session compared to the training session. In other words, why did the feedback condition not increase her control of the BCI compared to the non-feedback condition? In our opinion, two issues might be of relevance here.

First, the auditory feedback might have impaired performance for several reasons. The output of the classifier was biased to the left. In other words, the distribution of the probabilities, which the classifier generated during the test session, was skewed to the left. In practice, this meant that the classifier had a bias for left hand movements even though it were right hand taps. We corrected for the biased output of the classifier off-line and recomputed the probabilities. After this correction, the skewness of the probabilities disappeared. The bias in the output of the classifier might have hindered the participant to fully profit from the feedback in learning to control the side on which the 'tick' was presented.

In addition, subjects might benefit more from the feedback if the translation from classification probability to location is not calculated linearly, since small changes in location of the 'tick' were hard to detect if it was presented on both the left and the right loudspeakers. It might be better to increase the slope of the translation function at classification probabilities around 50 percent, i.e. in the situation in which the classifier can hardly discriminate whether it was a right or left hand movement.

Last, although Nijboer and colleagues (2008) reported auditory feedback to lead to approximately the same level of performance as visual feedback, they also observed that auditory feedback required longer training to reach an adequate level of performance than visual feedback. In their study, sixteen healthy participants learned to control their SMR. Auditory feedback was realized by either harp sounds for ERS or bongo sounds for ERD. The loudness of the sounds corresponded to the amount of modulation of the EEG signal. Nijboer et al. (2008) attempted to answer the question why visual feedback is superior to auditory feedback. The study of Hinterberger et al. (2004a), in which the effect of auditory versus visual feedback in learning to regulate SCPs was investigated, already suggested that auditory stimuli used as feedback about SCP changes might have been distracting for the participants. Hence, Nijboer and co-workers (2008) speculated that the lower initial performance with auditory feedback might have been due to an increased attentional demand. In addition, the authors hypothesized that participants were better able to extract information from the visual than from the auditory modality, since people rely heavily on guiding their actions through the visual system in daily life.

In contrast to the study of Nijboer et al. (2008), we used a more intuitive way of auditory feedback. Specifically, the 'tick' sound at the right side of the subject indicated that the classifier decided for a right hand movement and vice versa. One might expect it to be easier to associate the feedback to the correct hand in this way as compared to the harp and bongo sounds used in the experiment of Nijboer et al. (2008). Unfortunately, however, the present results do not show a positive effect of the auditory feedback. After the training session, the classification rate of Subject 1 dropped roughly to chance level. The subject probably had to get used to the feedback at this point, considering that this was her first BCI experiment. Over time, the performance recovered to a level of up to 80 %, which was as good as the classification rate in the training session. However, the question remains why the subject did not increase her performance to a higher level.

The second issue, which might have played a role here, concerns the learning process itself. Two aspects might have hampered the learning process of Subject 1. The subject already performed 87 % on the training session. It is possible that a ceiling effect occurred in this situation. In other words, the subject performed already at a rather high level in the training session, leaving no room for improvement. More likely, one session might not be enough to show a learning effect. This was also pointed out by Blankertz et al. (2008) after conducting a one-session BCI experiment. Moreover, most BCI studies using sensorimotor rhythms as discriminative brain patterns required multiple sessions to observe a learning effect (Pfurtscheller et al., 2006; Pfurtscheller et al., 2006b; Wolpaw & McFarland, 2004).

Until now, we only discussed the results of actual movement, not of mental imagery. Only Subject 2 performed significantly above chance level in imaginary movement. The TFRs of this subject showed an alternating pattern of ERD and ERS. Furthermore, the main focus of the power modulations was localized at the central electrodes. At these electrodes, no clear lateralization was observed in imagined movement, which is consistent with previous studies (Pfurtscheller et al., 1997; Geuze et al., 2007). In addition, the largest power fluctuations were found between 24 and 33 Hz, which was higher than expected, since the μ and β rhythm contain frequencies between 8 and 12 Hz and 18 and 26 Hz respectively. The classification performance on the training session was 58 %. According to the definition by Wolpaw as described in Kronegg, Alecu and Pun (2003), this performance can be translated into a bitrate of 1.1 bits/min based on a time interval of 1 second with two classes. We did not investigate the learning effect in this case, since the initial performance was already too poor and not likely to increase over time.

Obviously, the main questions here are: how can we increase the classification rate and how can we extract useful features from the subjects who did not show any significant results? The second question can be formulated more generally by asking how the problem of SMR-based BCI illiteracy can (partly) be solved. Nijholt and co-authors (2008) give us a clue by stating that in certain subjects some classes, i.e. types of imagined movement, are detectable and others are not. This implies that subject-specific classes should be chosen based on the training session. Blankertz and co-workers (2006, 2007, 2008) already did so by letting the subjects imagine right hand movement, left hand movement and right foot movement during a calibration session. Subsequently, the data were investigated by the experimenter to identify the two classes that gave best discrimination. They found that 12 out of 14 BCI-naïve subjects, i.e. 86 % of the subjects, reached a performance level of >70 % (Blankertz et al, 2008). The proportion of successful subjects is only slightly higher than the 80 % mentioned by Nijholt et al. (2008), indicating that selecting two classes out of several possible imagined movements reduces the problem of SMR-based BCI illiteracy a little. The group of Blankertz (2008) also points to the answer to the first question posed in this paragraph. Besides choosing two motor imagery classes out of three, selecting subject-specific frequency bands for classification might also greatly increase performance. Moreover, it was shown that using spatial filters improved performance drastically. When using spatial filters, one could use the typical topographies seen in movement imagery more optimally.

In conclusion, the current data do not convincingly show that time-locked imaginary hand tapping works as a paradigm in an on-line BCI setting. Only one subject performed significantly on imagined movement, though too poor to set up a test session, in which the suitability of the feedback could be tested. Future work should focus on implementing three classes in the training session to make the problem of illiteracy smaller. It is also worthwhile to investigate the effects of frequency band selection and the use of spatial filters. In addition, optimizing the auditory feedback or switching to visual feedback might improve learning of the subject. Also, to fully be able to investigate the learning effect, the participants should perform more than one test session.

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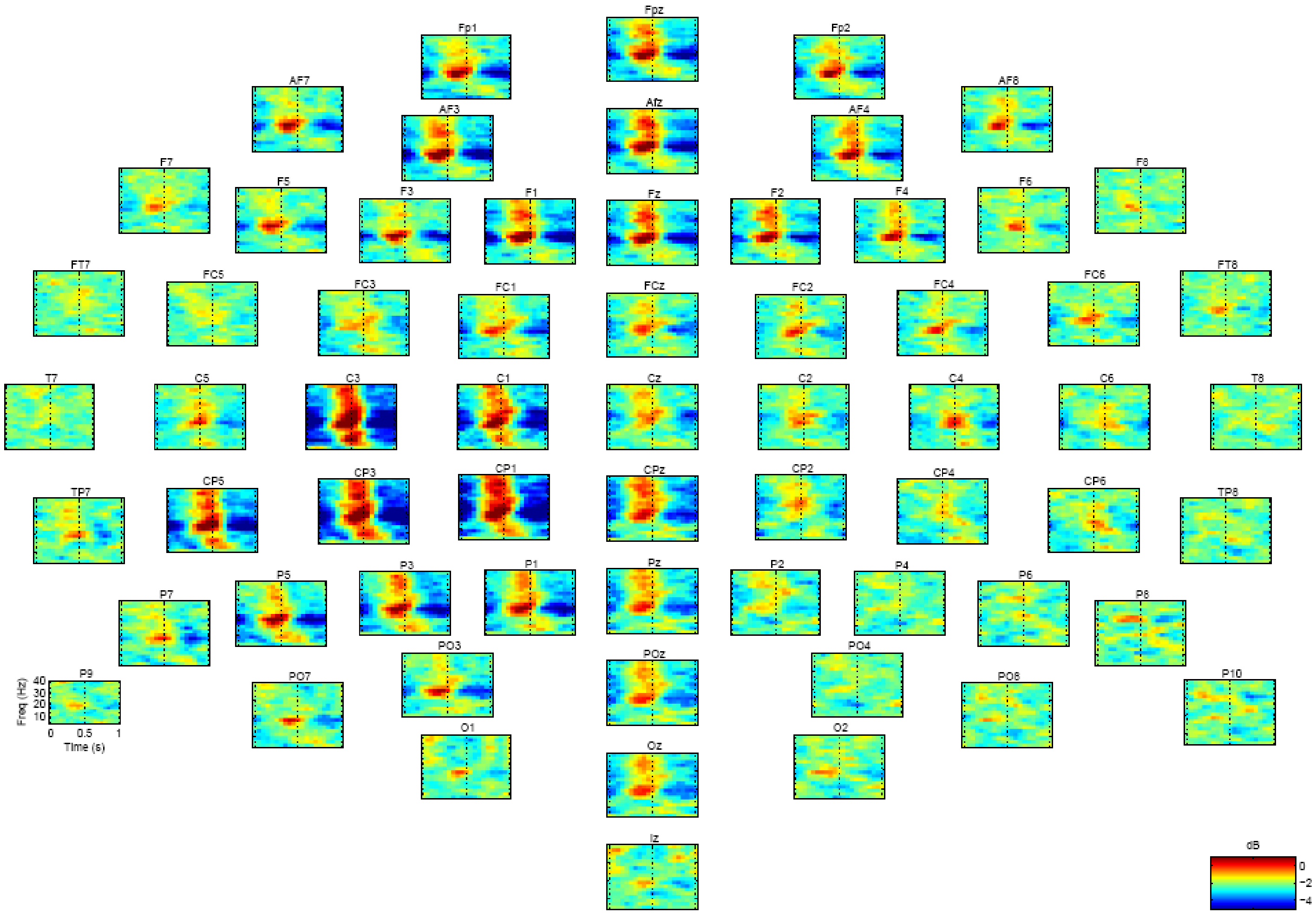

Figure 8. Overview of the TFR data of actual right hand movements of Subject 1. 256 Channels were down-sampled to a 64-channel layout. In each panel, the x-axis denotes time (s) in which one movement cycle is plotted, i.e. 0 - 0.5 s is the rest period and 0.5 - 1 s is the movement period. The dotted line indicates the transition between the two phases of the cycle. The y-axis denotes frequencies from 5 to 40 Hz. The power is scaled from -5 to 1 dB with the color map.

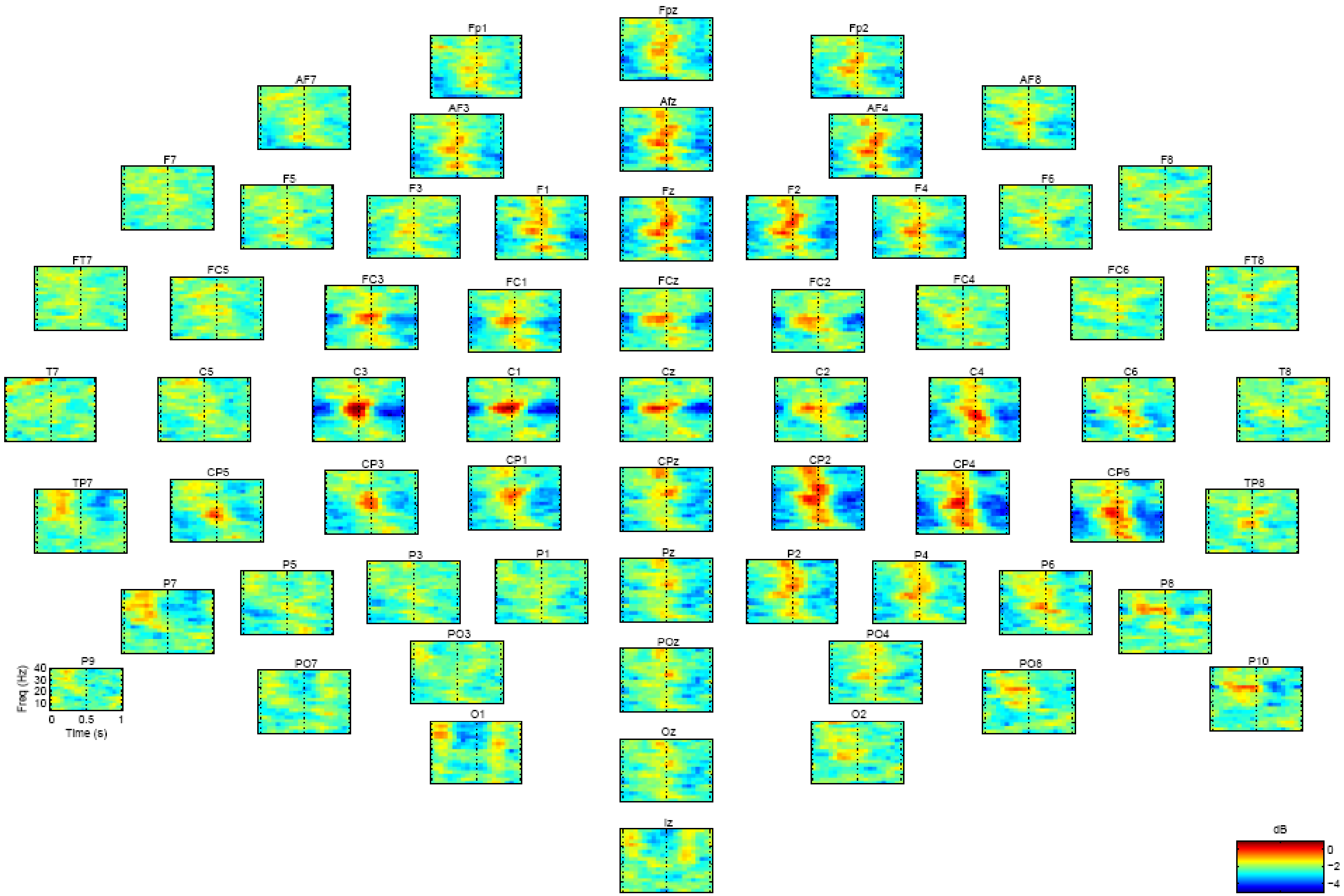

Figure 9. Overview of the TFR data of actual left hand movements of Subject 1. 256 Channels were down-sampled to a 64-channel layout. In each panel, the x-axis denotes time (s) of one movement cycle, i.e. 0 - 0.5 s is the rest period and 0.5 - 1 s is the movement period. The dotted line indicates the transition between the two phases of the cycle. The y-axis denotes frequencies from 5 to 40 Hz. The power is scaled from -5 to 1 dB with the color map.

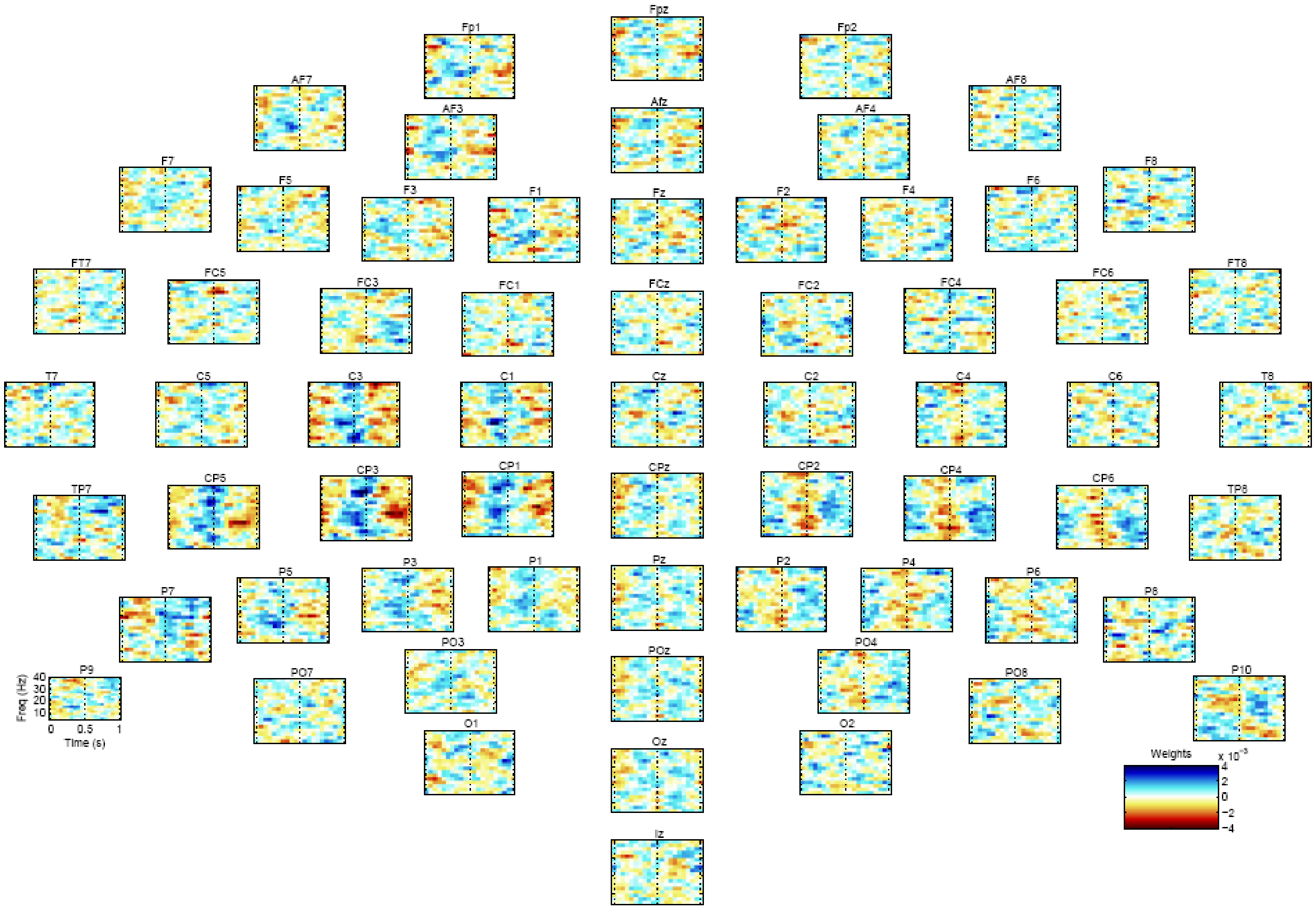

Figure 10. Overview of the weight vector determined by kernel logistic regression for each of the 64 channels separately. The x-axis denotes time (s) of one movement cycle, i.e. 0 - 0.5 s is the rest period and 0.5 - 1 s is the movement period. The dotted line indicates the transition between the two phases of the cycle. The y-axis denotes frequencies from 5 to 40 Hz. The weights are scaled between $-4\cdot10^{-3}$ to $4\cdot10^{-3}$ with the color map.

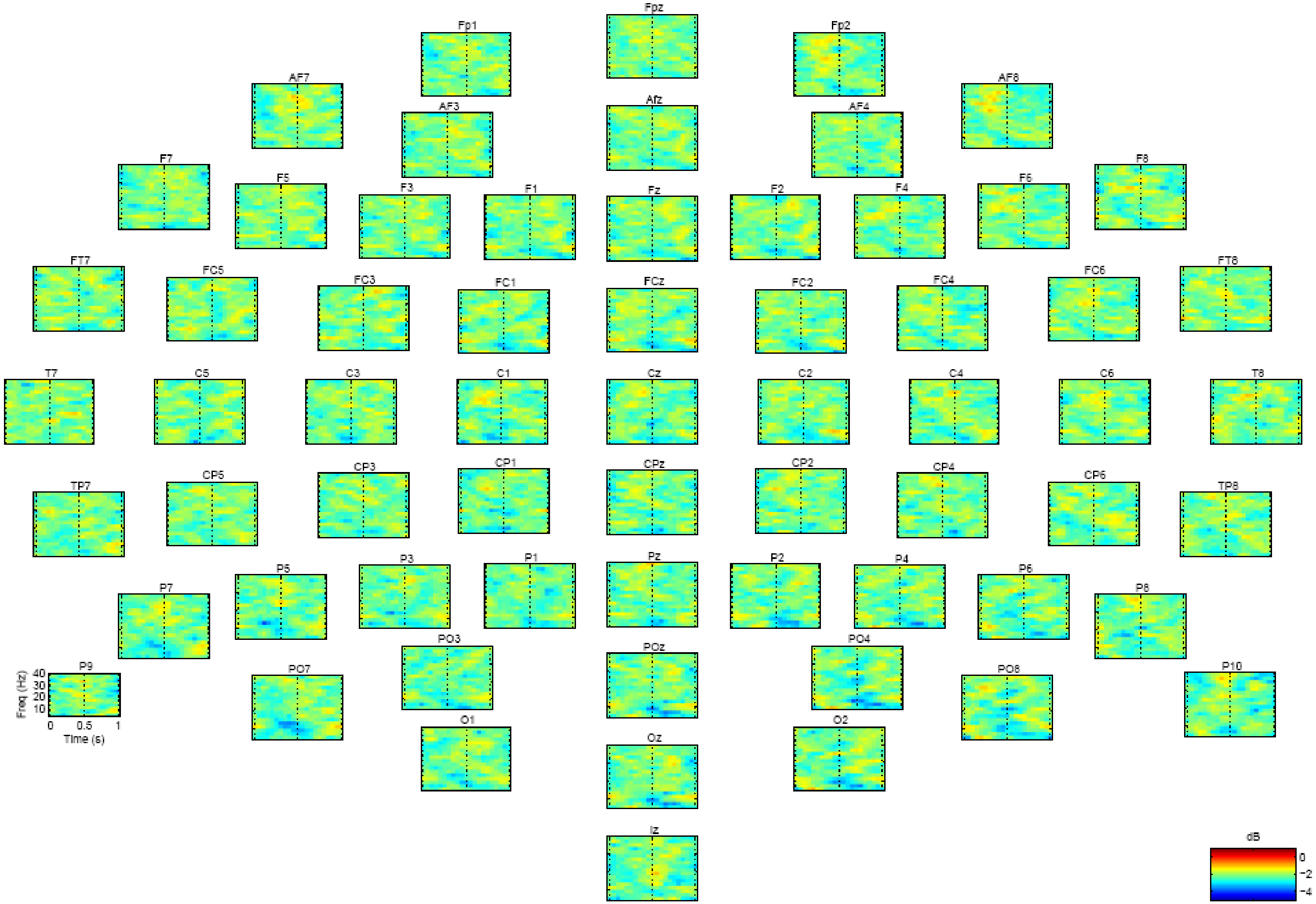

Figure 11. Overview of the TFR data of imagined right hand movements of Subject 2. 256 Channels were down-sampled to a 64-channel layout. In each panel, the x-axis denotes time (s) for one imagery movement cycle, i.e. 0 - 0.5 s is the rest period and 0.5 - 1 s is the imagery period. The dotted line indicates the transition between the two phases of the cycle. The y-axis denotes frequencies from 5 to 40 Hz. The power is scaled from -5 to 1 dB with the color map.

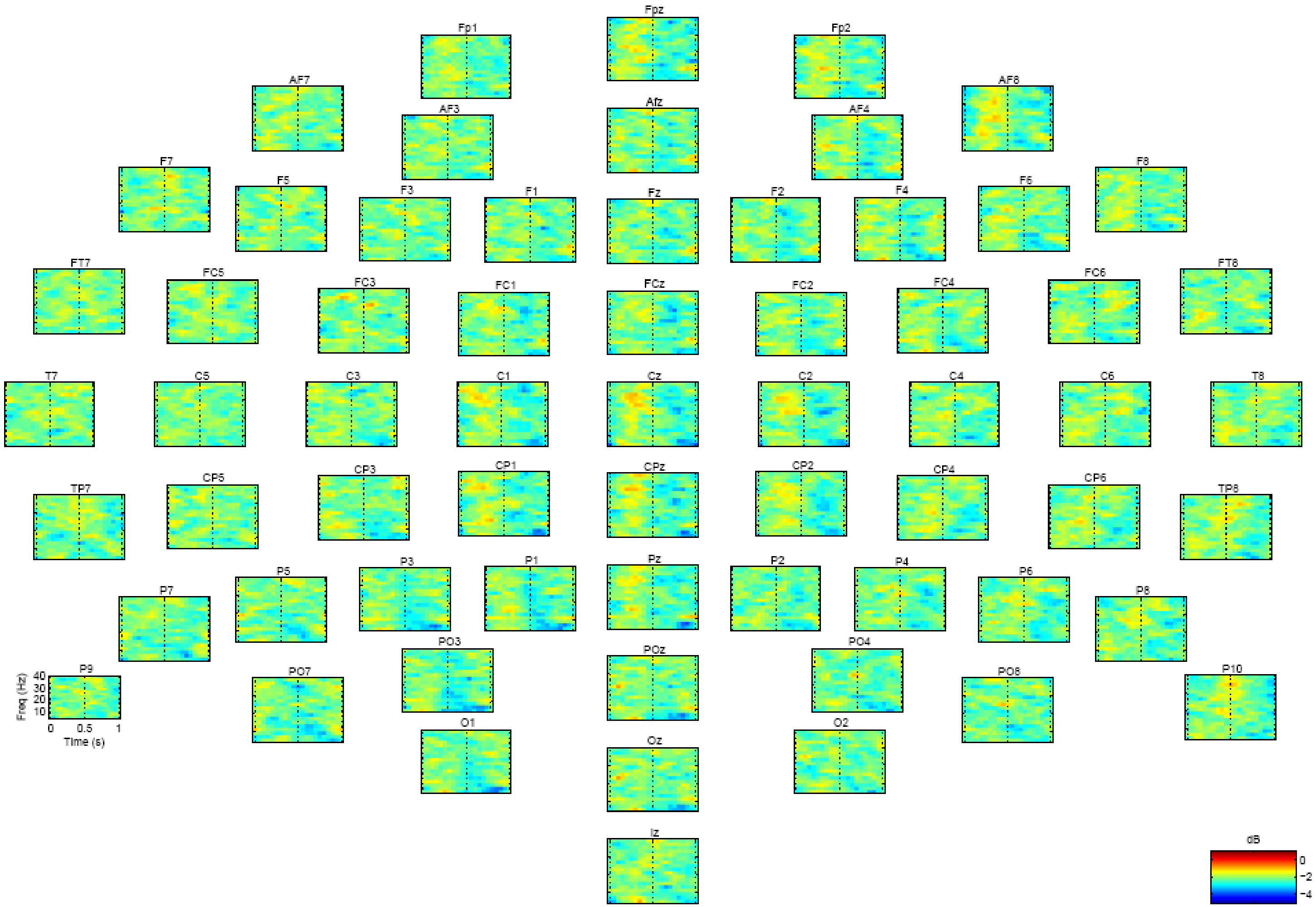

Figure 12. Overview of the TFR data of imagined left hand movements of Subject 2. 256 Channels were down-sampled to a 64-channel layout. In each panel, the x-axis denotes time (s) for one imagery movement cycle, i.e. 0 - 0.5 s is the rest period and 0.5 - 1 s is the imagery period. The dotted line indicates the transition between the two phases of the cycle. The y-axis denotes frequencies from 5 to 40 Hz. The power is scaled from -5 to 1 dB with the color map.