Neurophysiological Predictor of SMR-Based BCI Performance

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Abstract

Brain-Computer Interfaces (BCIs) allow a user to control a computer application by brain activity as measured, e.g., by electroencephalography (EEG). After about 30 years of BCI research, the success of control that is achieved by means of a BCI system still greatly varies between subjects. For about 20% of potential users the obtained accuracy does not reach the level criterion, meaning that BCI control is not accurate enough to control an application. The determination of factors that may serve to predict BCI performance, and the development of methods to quantify a predictor value from psychological and/or physiological data serves two purposes: a better understanding of the 'BCI-illiteracy phenomenon', and avoidance of a costly and eventually

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Preprint submitted to NeuroImage *March 8, 2010*

frustrating training procedure for participants who might not obtain BCI control. Furthermore, such predictors may lead to approaches to antagonize BCI-illiteracy. Here, we propose a neurophysiological predictor of BCI performance which can be determined from a two minutes recording of a 'relax with eyes open' condition using two Laplacian EEG channels. A correlation of $r = 0.53$ between the proposed predictor and BCI feedback performance was obtained on a large data base with $N = 80$ BCI-naive participants in their first session with the Berlin Brain-Computer Interface (BBCI) system which operates on modulations of sensory motor rhythms (SMRs).
Key words: Brain-Computer Interface (BCI), Sensory Motor Rhythms (SMRs), Event-Related Desynchronization (ERD), Neurophysiological Predictor, BCI Illiteracy

Introduction

Amplitude modulations of sensory motor rhythms (SMRs) can be voluntarily controlled by most subjects, e.g., by imagining movements. Recently evidence was provided that also patients diagnosed with amyotrophic lateral sclerosis (ALS) can accomplish SMR modulations (Kübler et al. (2005)). This ability can be taken as a basis for Brain-Computer Interfaces (BCIs) which are devices that translate the intent of a subject, as derived from measuring brain signals, directly into control commands, e.g., for a computer application or a neuroprosthesis (Dornhege et al. (2007); Allison et al. (2007); Birbaumer et al. (2006); Pfurtscheller et al. (2005); Wolpaw et al. (2002); Kübler et al. (2001)). For alternative applications of BCI technology, see Kohlmorgen et al. (2007); Müller et al. (2008); Gerson et al. (2006); Tangermann et al.

(2009). More specifically, SMR-based BCI operation has its neurophysiological grounds in the observation that macroscopic brain activity during resting wakefulness is comprised of distinct 'idle' rhythms located over distinct brain areas, e.g., the parieto-occipital α-rhythm (8–12 Hz), cf. Berger (1933). The perirolandic sensorimotor cortices show rhythmic macroscopic EEG oscillations (μ-rhythm) (Jasper and Andrews (1938); Hari and Salmelin (1997)), with spectral peak energies at about 9–14 Hz localized predominantly over the postcentral somatosensory cortex. Typically phase coupled components can be found in the beta band (16–25 Hz) over the precentral motor cortex. Modulations of the μ-rhythm have been reported for different manipulations, e.g., motor activity, both actual and imagined (Jasper and Penfield (1949); Pfurtscheller and Aranibar (1979); Schnitzler et al. (1997)), as well as somatosensory stimulation (Nikouline et al. (2000)). Trial averages of μ-rhythm power reveal attenuation of SMR, termed event-related desynchronization (ERD, Pfurtscheller and da Silva (1999)), or increase (event-related synchronization, ERS). Typically, ERD indicates cortical activity, while ERS is observed as a rebound after ERD or during cortical idling (Pfurtscheller and da Silva (1999); Pfurtscheller et al. (2006)).

Several EEG-based BCI systems rely on voluntary modulations of SMRs, e.g., by imagining movements as explained above. Fig. 1 shows the power spectral density (in particular the amplitude of SMRs) in two channels over the hand areas of the sensorimotor cortex during left hand and right hand motor imagery and the corresponding topographies.

However, due to large inter- and intra-subject variability of the frequency band and spatial patterns of SMR modulation, most SMR-based BCI systems

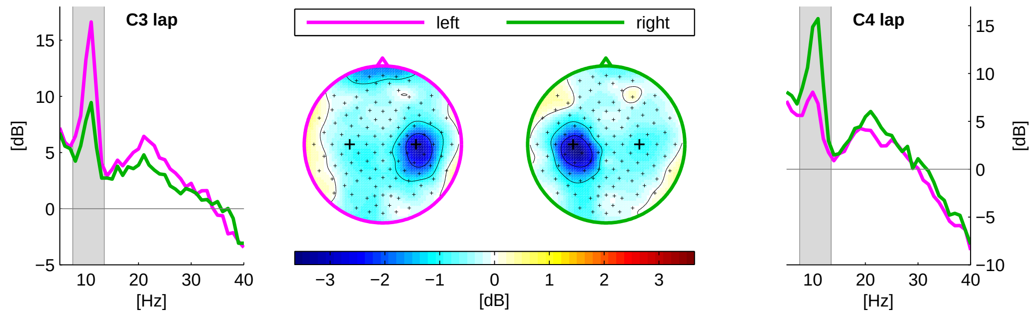


Figure 1: Modulated power spectral density during motor imagery of left and right hand in participant *kg*. The shaded area indicates the frequency range that was used for BCI feedback. The maps show the topographical distribution of band-power in the selected frequency range for left and right hand movement imagery conditions. Band-power during the reference interval -2000 to 0 ms was subtracted to obtain the maps. It is important to note that such prototypical patterns of band power can only be observed in a minority of participants.

require several training sessions in which participants learn the ability to modulate their SMR appropriately to control a BCI application (Wolpaw and McFarland (2004); Kübler et al. (2005); Vidaurre et al. (2006)). Other approaches are able to provide BCI control already in the very first session, but still need a calibration period of about 30 minutes (Guger et al. (2000); Blankertz et al. (2008a, 2007)). Additionally, some of those latter systems typically use many electroencephalography (EEG) channels which require a substantial amount of time for preparation with current sensor technology. However, new experimental dry sensors have been demonstrated successfully for BCI use (Popescu et al. (2007)).

One of the biggest challenges in BCI research is to solve the problem of BCI illiteracy[1], which is that BCI control fails to work for a non-negligible proportion of participants (estimated 15% to 30%). The development of predictors of BCI performance may serve to gain a deeper understanding of this phenomenon. Until the problem of BCI-illiteracy is solved, such predictors may also serve to avoid the frustrating and costly procedure of trying to establish BCI control. On the other hand, the study of predictors of BCI performance may lead to novel approaches, e.g., training procedures or alternative experimental designs, which antagonize some causes of illiteracy and thereby help to provide more people with the possibility of BCI communication.

Some literature exists on predictors of performance with a BCI system based on the control of slow cortical potentials (SCPs, Elbert et al. (1980)). A correlation of the ability for implicit learning with BCI performance was found in Kotchoubey et al. (2000). Other work demonstrated the correlation between performance in early neurofeedback sessions with the success to control a BCI application in later sessions (Neumann and Birbaumer (2003), Kübler et al. (2004)). In Daum et al. (1993) a correlation between attention span tests and the ability to learn SCP regulation was found in a study with 14 participants with epilepsy.

Regarding SMR-based BCIs, to our knowledge Burde and Blankertz (2006) was the only approach to predict feedback performance. In that work a significant ($\alpha = 0.05$) correlation of $r = 0.59$ was found between the psychological

[1] By the term 'BCI illiteracy' we denote the case that a BCI system fails to correctly detect the mental state of its user.

variable ‘locus of control with regard to technology’ (Beier (2004)) and BCI feedback performance in a group of $N = 17$ participants.

The aim of the current study was to develop a neurophysiological predictor for a participant’s performance of operating an SMR-based BCI. As we wanted to draw conclusions that generalize beyond the investigated sample, we included a large corpus of $N = 80$ BCI-naive participants. We propose a resting EEG-based neurophysiological- mathematical procedure with high predictive quality for later BCI performance. Additionally, our approach is effective with respect to cap montage and recording time. Finally we provide interpretable insight into the neurophysiological reasons for good resp. bad BCI performance and BCI illiteracy.

Material and methods

Experimental Setup

Eighty healthy BCI-novices (41 female, age 29.9±11.5 years; 4 left-handed) [Requirements: full contractual capability, mother tongue German (since a series of psychological tests had to be accomplished), no neurological disease, e.g., epilepsy] took part in this one-session study. All measurements (calibration and feedback runs) of a participant were recorded on the same day (one ‘session’). Subjects were paid 8 EUR per hour for the participation in the study.

The participants were sitting in a comfortable chair with arms lying relaxed on armrests. Brain activity was recorded from the scalp with multichannel EEG amplifiers (BrainAmp DC by Brain Products, Munich, Germany) using 119 Ag/AgCl electrodes (reference at nasion; manufacturer

EasyCap, Munich, Germany) in an extended 10-20 system, and sampled at 1000 Hz with a band-pass of 0.05 Hz to 200 Hz. Additionally, we recorded electromyogram (EMG) from both forearms and the right leg as well as horizontal and vertical electrooculogram (EOG). The EMG/EOG channels were exclusively used to control for physical limb/eye movements that could correlate with the task and could be reflected directly (artifacts) or indirectly (afferent signals from muscles and joint receptors) in the EEG channels.

The session started with an EEG artifact recording during which the participant performed tasks such as particular eye movements, blinking, or maximum voluntary contraction of the hand. Then, ten periods of 15s were recorded with the alternating tasks to 'relax with eyes open' and to 'relax with eyes closed'.

After this baseline recording and at the very end of the experimental session, one run with the task 'observation of movements' was recorded. Video clips of 10s duration showed either left hand, right hand or feet movement from a first person's perspective, which were presented in random order, 20 of each type. Results of the observation task will be presented elsewhere.

During 'calibration' every eight seconds one of three different visual cues (arrows pointing left, right, or down) indicated to the participant which type of motor task to perform: left hand, right hand, and right foot or feet movement (according to the preference of the participant), see Fig. 2. A 15s break followed after every 20 trials. In one run, 25 trials of each motor condition were recorded. First, we recorded one run of performed movements (results will be presented elsewhere) and subsequently three runs of imagined movement resulting in 100 trials altogether.

Between the calibration runs of imagined movement, participants were confronted with a computerized version of the d2-test (Brickenkamp and Zillmer (1998)), which was part of an extended psychological test battery (results will be presented elsewhere).

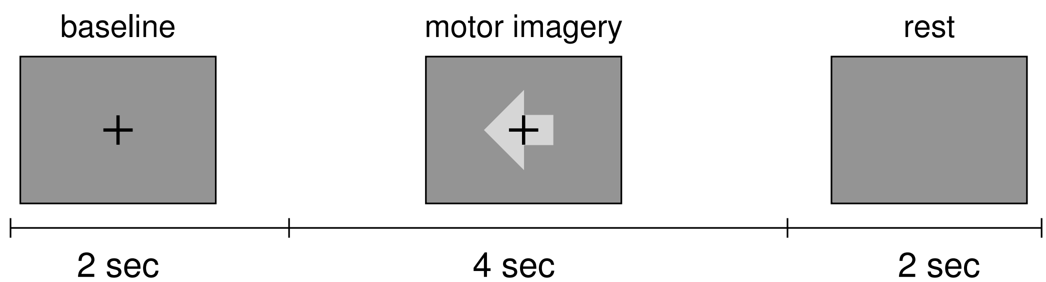


Figure 2: Course of a calibration trial. 2s fixation cross, 4s motor imagery cued by arrows (left, right, or down), 2s blank screen.

After the calibration, participants performed three runs each of 100 trials with BCI 'feedback' (for some participants only one or two runs were recorded due to fatigue ($N = 3$) or lack of time ($N = 7$)). The first 20 trials were used for adapting the bias of the classifier (see section '*BBCI Feedback*'). Each trial of feedback started with a period of 2s with a black fixation cross in the center of a gray screen. Then an arrow appeared behind the cross to indicate the target direction of that trial (left or right for motor imagery classes *left hand* and *right hand* and downward for class *foot*) and 1s later the cross turned purple and started moving according to the classifier output, as described in section '*BBCI Feedback*'. If the foot classes was selected, the cursor moved on a corner shaped trajectory: For *left hand* vs. *foot*, e.g., the cursor moved from the center to the left of the screen for detected *left hand* motor imagery, and the cursor moved from the center downwards for detected *foot* imagery. After 4s of cursor movement the cross froze at the final position and turned black again. Two seconds later the cross was reset to the center position and the next trial began. Hits or misses were counted according to this final position, but the score was only indicated during a break of 15s after every block of 20 trials (see Fig. 3 for timing during feedback runs).

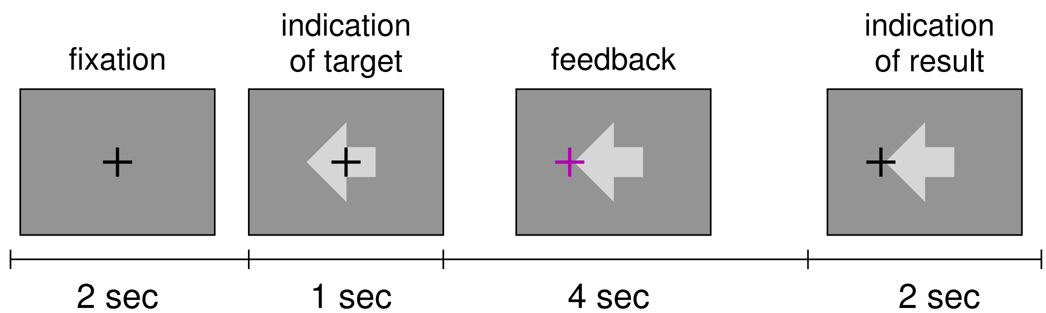


Figure 3: Course of a feedback trial. 2s fixation cross (black), 1s indication of target direction cued by arrows, 4s feedback (cross turns magenta and moves according to BBCI classifier), 2s indication of result (cross turns black and freezes at its final position).

BBCI Feedback

The EEG signals of the calibration measurement were band-pass filtered in a subject-specific frequency band and temporally filtered in a subject-specific time interval. The start of that interval varied between 480 ms and 2720 ms (median 930 ms) after cue onset and its end varied between 1700 ms and 4990 ms (median 3810 ms). The median length of the interval was 2730 ms (range 1000 ms to 3890 ms). Details on the heuristics underlying the selection of frequency band and time interval can be found in Blankertz et al. (2008b). Note that also subject-optimized spatial filters were determined by common spatial pattern (CSP) analysis (Blankertz et al. (2008b)). From these signals the log-variance was calculated in each trial of the calibration data. This procedure resulted in a feature vector with dimensionality equal to the number of (heuristically) selected CSP filters (Blankertz et al. (2008b)). To our experience, those features can be classified well by linear methods like linear discriminant analysis (LDA). Other paradigms and feature representations may however require non-linear modeling (see, e.g., Müller et al. (2001); Müller et al. (2003)).

For online operation, features were calculated every 40 ms with a sliding window of 750 ms (applying CSP filters, band-pass filtering, calculating log-variance and applying the LDA classifier, see Blankertz et al. (2008b)). The output of the classifier was translated into cursor movement in a rate control manner: At the beginning of each trial, the cursor started in the center of the screen and every 40 ms a fraction of the classifier output was added to the current cursor position (see also section '*Experimental Setup*'). CSP filters calculated from the initial calibration measurement were not adapted during online operation. The bias of the linear classifier was adapted on the basis of the data of the first 20 trials of each feedback run (see Krauledat et al. (2008)). (By bias we denote the term b in the separating hyperplane formulation $y = \boldsymbol{wx} + b$ which can be used to adjust the output of a binary classifier toward one class or the other). These 20 trials were not included in the calculation of the feedback performance.

Performance Predictor

To construct our novel SMR predictor, only a short two minutes recording of EEG under the condition 'relax with eyes open' using two Laplacian channels (C3 and C4, calculated from nine original monopolar channels) was required. For this purpose we used the concatenated segments of the same condition during the baseline recording (see section '*Experimental Setup*').

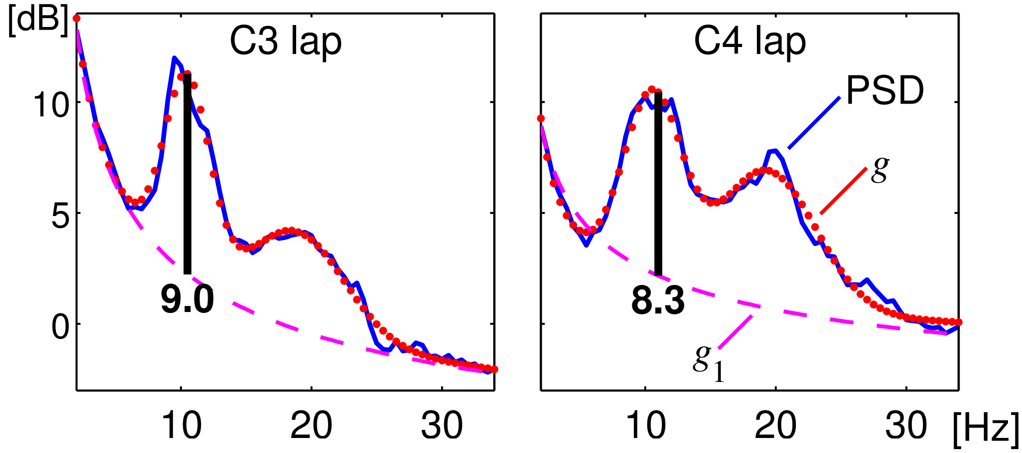


Figure 4: Illustration of the calculation of the performance predictor. The plots depict the power spectral densities (PSDs) of a relax measurement (eyes open) of one participant for two Laplace-filtered channels over sensorimotor cortex (solid blue line), the estimated noise floor $g_1(f; \lambda, \mathbf{k})$ (dashed purple line) and the fitted values $g(f; \lambda, \mu, \sigma, \mathbf{k})$ (dotted red line). In each channel the maximum elevation of the peaks over the noise floor was determined (vertical black lines). The value of the SMR predictor is the average of these two values, in this example $(9.0 + 8.3)/2 = 8.65$.

From these data we calculated the power spectral density (PSD) in the Laplace-filtered channels C3, C4 and determined for each of those channels the maximum difference between the PSD curve and a fit of the $1/f$ noise spectrum as explained below (cf. Fig. 4). These two values were estimates of the strength of the SMR over the hand areas. The SMR-predictor was calculated as the average of those two values. It quantified the potential for desynchronization of the SMRs at rest as an indicator of SMR strength during feedback.

We modeled each PSD curve as a function g of the frequency f with two additive components of the form

$$g(f; \lambda, \mu, \sigma, \mathbf{k}) = g_1(f; \lambda, \mathbf{k}) + g_2(f; \mu, \sigma, \mathbf{k}) \qquad \text{with}$$
$$g_1(f; \lambda, \mathbf{k}) = k_1 + \frac{k_2}{f^\lambda} \qquad \text{and}$$
$$g_2(f; \mu, \sigma, \mathbf{k}) = k_3\varphi(f; \mu_1, \sigma_1) + k_4\varphi(f; \mu_2, \sigma_2),$$

where $\mathbf{k} = (k_1, k_2, k_3, k_4) \in \mathbb{R}^4$, $\lambda \in \mathbb{R}$ and $\varphi(\cdot; m, s)$ denotes the probability density function (pdf) of a normal distribution with mean m and standard deviation s. Function g_1 is a model for the noise spectrum.The parameters λ and k_2 determine its shape and k_1 its power level. Function g_2 models the additional peaks in the PSD around α and β frequency ranges. Thereby, μ_1 resp. μ_2 are the corresponding location parameters, σ_1 resp. σ_2 the scale parameters and k_3 resp. k_4 determine the amplitudes of the two peaks. As objective function for the optimization of the nine parameters ($\lambda, \mu = (\mu_1, \mu_2), \sigma = (\sigma_1, \sigma_2)$, and $\mathbf{k}$) we chose the L_2-norm of the difference vector $PSD(\mathbf{f}) - g(\mathbf{f}; \lambda, \mu, \sigma, \mathbf{k})$, where $\mathbf{f}$ is the vector of all available frequency values for the PSD; in our case $\mathbf{f} = (2Hz, 3Hz, \ldots, 35Hz)$, see Fig. 4.

Since we decomposed the PSD into the noise component g_1 and the two peak components g_2, the contribution of one channel to our proposed indicator was simply $\max_{f\in\mathbf{f}} g_2(f; \mu, \sigma, \mathbf{k}) \approx \max_{f\in\mathbf{f}}\{PSD(f) - \text{noise}(f)\}$. It is worth noting that this PSD model with additive components g_1 and g_2 provides distinctly higher predictive accuracy than a simpler model which does not explicitly take into account the noise floor of the PSD. For example, averaging the peak PSD values in channels C3 and C4 without subtracting the corresponding estimated noise floor values led in our sample to a deterioration of the correlation coefficient with BCI feedback performance from 0.53 to 0.33.

Determining Foci of SMRs

We used two methods for determining which channels were best suited for the SMR predictor, one based on the *relax* condition, the other based on the separability of the *motor imagery* conditions. Using the data of the *relax* condition of each participant, we did the same optimization as explained in section '*Performance Predictor*' for the SMR predictor to quantify separately the strength of the SMR rhythm in each Laplacian channel. The obtained values were averaged across all 80 participants.

Using the data of the *motor imagery* conditions, we determined the classification error for each participant when using logarithmic band power in a single Laplacian channel as a feature. Here, a classifier was trained on the data of the calibration measurement and evaluated on the feedback measurement data. The resulting values were averaged across participants who had the same combination of motor imagery classes in the feedback (*left-right* (LR) for $N = 30$, *left-foot* (LF) for $N = 34$, and *foot-right* (FR) for $N = 16$ participants).

Results

BBCI Feedback

Feedback accuracy varied largely between participants (mean 74.4% ± 16.5%), covering the full range from chance-level performance (50%) to perfect control (100%), see Fig. 5. For most participants performance also varied strongly between runs. More specifically, the intra-participant performance variability between runs ranged from 0% to 19.8% (mean 5.3% ± 3.7%).

On average, feedback performance decreased from run to run (medians of subjects who completed all three runs: 77.5% – 75% – 68.8%). Self-assessed fatigue increased on average within the three feedback runs (2.8 – 3.3 – 3.8 on a scale from 1 to 7).

Selection of Channels for the SMR Predictor

Scalp maps of the grand average amplitudes of local rhythmic activity are displayed in Fig. 6a. The focus of the SMR of the left and the right hand was at location C4 and C3, respectively. No consistent SMR focus was found over the foot area.

Scalp topographies of the grand average classification error, when using single-channel features, are shown separately for the three binary combinations of motor imagery conditions in Fig. 6b. For combinations LR (*left-right*) and LF (*left-foot*), positions C3 and C4 were the foci of the lowest classification error. For combination FR (*foot-right*) there was only one focus of minimal classification error, which was between positions C3 and CFC3 (CFC3 is located in the middle between C3 and FC1).

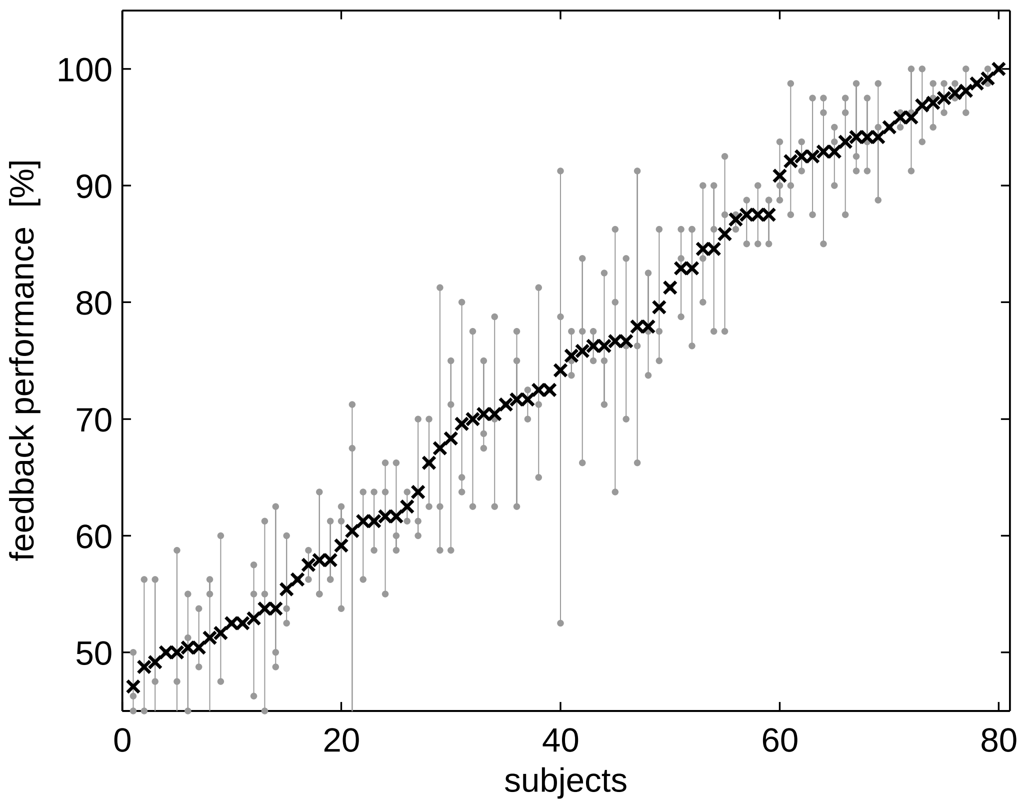
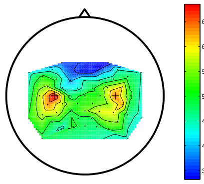


Figure 5: Feedback Performance. The black crosses show the feedback performance averaged over all recorded runs for each participant. Connected gray dots indicate the corresponding accuracy per run.

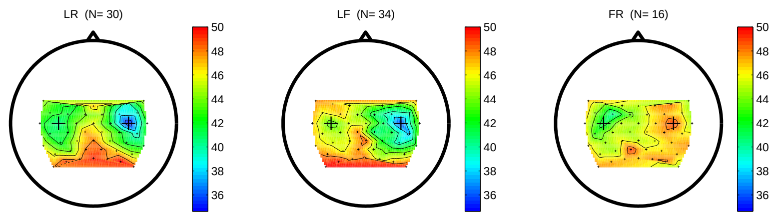
Performance Predictor

In Fig. 7, the values of the proposed SMR-predictor are plotted against the BCI feedback performance.

A correlation coefficient (Pearson) of $r = 0.53$ was obtained. This means that the SMR predictor explained as much as $r^2 = 28\%$ of the variance in feedback accuracy in our sample of $N = 80$ participants. To obtain a more robust correlation analysis data were trimmed (Huber and Ronchetti (2009))



(a) Idle Rhythm



(b) Topographies of error-rates in single-channel classification for class combinations LR, LF, and FR

Figure 6: (a) Topography of the SMR idle rhythm. For each Laplacian channel the amplitude of the idle rhythm during a *relax* condition was calculated as in the proposed SMR predictor (see section '*Performance Predictor*').The resulting values were averaged across all 80 participants and displayed as scalp topography. Larger crosses mark the channels C3 and C4. (b) Average classification error utilizing only one Laplacian channel per motor imagery class. For each binary combination of motor imagery classes *left-right* (LR), *left-foot* (LF), and *foot-right* (FR), the classification error in single Laplacian channels was determined, averaged across participants for whom the respective class combination was chosen for feedback and displayed as scalp topographies. Larger crosses mark the channels C3 and C4.

by removing points of the sample that have the 10% largest Malahanobis distances to the data center (consisting of the arithmetic means of the SMR predictor and the BCI feedback performance values). Applying this technique results in removal of the data points which are shaded in Fig. 7 and in an increase of correlation to $r = 0.61$.

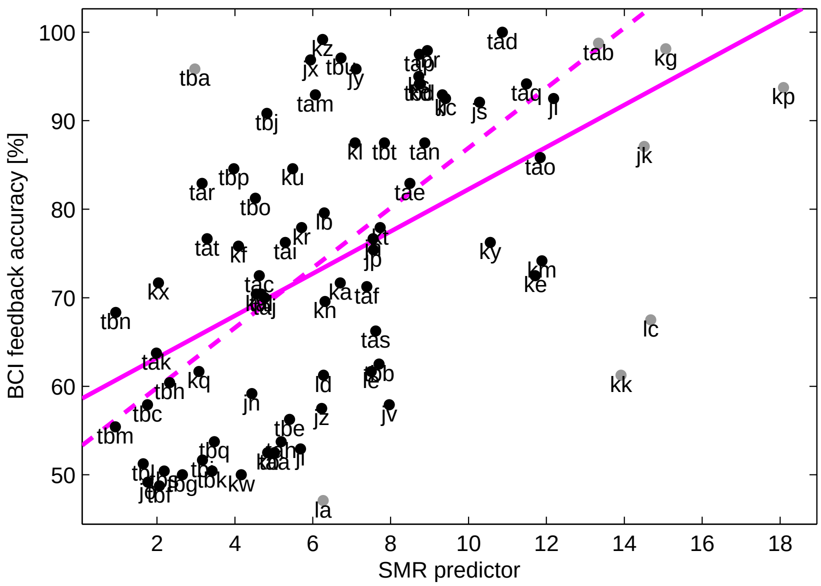


Figure 7: Correlation of SMR-predictor with BCI performance. Each dot corresponds to one participant. The value of the proposed SMR-predictor (abscissa) is plotted against the average BCI feedback performance (ordinate). The solid line is the result of a linear regression analysis of the BCI performance onto the SMR-predictor ($r = 0.53$, Pearson correlation). The slope parameter of this regression line was estimated as $\hat{\beta} = 2.38$. This has the interpretation that the expected increase in BCI feedback accuracy in case that the predictor value increases by one unit equals 2.38%. Removing outliers by trimming with a level of 10% (shaded points) increases the Pearson correlation coefficient to $r = 0.61$ (corresponding regression line dashed, $\hat{\beta} = 3.39$).

Discussion

BBCI Feedback

Feedback results of 77.5% on average were remarkably high for first-time BCI users in their first run. Notably, even better results have been obtained in earlier studies Blankertz et al. (2007, 2008a). This can be understood from the fact that the demands were high on the participants in this study. Because we used 128 EEG/EMG/EOG channels, the preparation of the cap often took more than one hour. Then there was a sequence of several off-line measurements such that the actual feedback only started after several hours. The complete session took 5.5 to 6.5 hours. This may have had negative influence on the performance compared to the earlier studies which ere performed under more convenient conditions. Self-assessed fatigue increased and feedback performance decreased on average from run to run. This suggests that effects of fatigue were more prominent than potential improvement of performance by practice.

Selection of Channels for the SMR Predictor

Raw EEG scalp potentials are known to have a poor spatial resolution due to volume conduction. This implies the need for spatial filtering if the signal of interest is weak, like SMRs, compared to other potentials of the brain. If no prior data is available to optimize subject-specific spatial filters, Laplacian filters are a good first choice, see Blankertz et al. (2008b). Consequently, our aim was to operate with two or three Laplacian channels only to minimize the effort that is needed to predict BCI performance.

We conclude from our results that single Laplacian channels C3 and C4 are a reasonable choice for the SMR predictor. Those locations showed the strongest SMR amplitude in the *relax* condition and provided most information for the discrimination of the *motor imagery* conditions, see Fig. 6.

Peri-Imagery ERS

Several studies found an ERS during motor imagery ('peri-imagery ERS'). This ERS was typically located either ipsilateral during hand motor imagery, or bilaterally over both hand areas during foot motor imagery (Pfurtscheller et al. (2006)). One interpretation of the peri-imagery ERS is that it is a surround ERS reflecting an active inhibition of non-involved areas. Pfurtscheller and colleagues observed the peri-imagery ERS in motor imagery trials without feedback as in our offline calibration and the band power increased relative to a pre-stimulus interval. The peri-imagery ERS phenomenon might deteriorate the performance of our proposed SMR predictor provided that (1)during motor imagery band-power increases substantially over the level of a (longer lasting) *relax condition*, and (2) the phenomenon can also be observed during feedback operation. In this situation (weak SMR peak in the relax condition, but successfully control BCI feedback by an ERS) our SMR predictor would underestimate the BCI performance

In our data base of 80 participants, we found 51 cases of peri-imagery ERS (over pre-stimulus level) in at least one of the three motor imagery classes (mostly *foot*) during calibration, which is in line with Pfurtscheller et al. (2006). But, remarkably, only four of those still produced a substantial ERS during feedback operation. In three of these cases, the SMR predictor indeed underestimated the BCI performance; in the forth, the raise of the SMR peak above the *relax* level was of negligible magnitude, such that it did not matter for the SMR predictor. Another four participants were moderately successful in producing an ERS during feedback (mean BCI feedback accuracy 73%). Seventeen participants had an ERS relative to pre-stimulus level, which did not exceed the SMR level of the relax condition. Notably, 19 participants who had a peri-imagery ERS during calibration had none during feedback runs. For the seven remaining participants, the binary class combination that was chosen for feedback did not include the class for which an ERS was observed during calibration. Thus, it cannot be judged how many of those would have produced a similar peri-imagery ERS during feedback. However, since the selection of classes was based on classification performance during calibration, it can be concluded that the ERS effect was less reliable than the ERD.

To conclude, with respect to the proposed SMR predictor, we could not find evidence in our data that peri-imagery ERS caused a substantial source prediction error. However, the role of peri-imagery ERS during calibration has to be studied in more detail, in particular, why the phenomenon rarely carries over to the feedback condition.

Implications for the Illiteracy Problem and Limitations

The finding of our study suggests that the strength of the SMR idling rhythm in the EEG is an essential property for successful performance with an SMR-based BCI. This might be seen as a drawback of this type of BCI system. As one alternative, features derived from slow movement related potentials could be used, which are known to vary independently from SMR modulations, cf. Dornhege et al. (2004). On the other hand, the relationship that was found in this study may pave a way to approach the BCI illiteracy problem: further studies will evaluate a specifically tailored neurofeedback training to enhance the SMR idle rhythm and, hopefully, feedback performance in subsequent BCI applications.

While present results were restricted to data recorded within the same session, the intra-subject variability of SMR-predictor values as well as the relation of the predictor to performance in future BCI sessions need to be investigated in further studies. Likewise, the value of the SMR predictor in BCI approaches that require more individual learning by means of neurofeedback remains to be elucidated [Kübler et al. (2005); Neuper et al. (2003)]. Despite our SMR predictor being to date the strongest described in the neurofeedback/BCI literature, it has to be kept in mind that two-third of the variance is caused by other factors.

Cases of Prediction Failure

Our performance predictor essentially estimated the amplitude of the SMR to assess the potential for BCI performance assuming that motor imagery leads to an attenuation of the SMR (Pfurtscheller and da Silva (1999)). There were, however, several cases in which the SMR predictor failed. (1) Some participants had a detectable SMR but no class-specific attenuation of that rhythm. One possible reason for this phenomenon could be that these participants used a wrong strategy, e.g., only visually imagining the movements instead of kinesthetically (Neuper et al. (2005)). Participant *ji*, e.g., reported to have used abstract thoughts ("I rather thought *left* and *down*.") during feedback instead of motor imagery as in the calibration measurement. For this participant the actual feedback performance was at chance level, while the SMR predictor indicated fair performance. But the phenomenon of missing ERD was also observed in participants whose self-assessments provided no evidence for non-compliance with instructions. Here, an alternative approach suggested in Nikulin et al. (2008) could be useful: In this study, individuals were guided to perform *quasi-movements*, which are volitional movements that are minimized under instructions of the experimenter to an extent that they become undetectable by peripheral physiological measures. Although they are similar to imagined movements, the attitude of the performers is different. Classification rates (for left vs. right hand) were significantly better for quasi-movements than for imagined movements in a study with seventeen volunteers. Consequently, participants in who the BBCI fails to detect task related ERD could be instructed to perform quasi movements. Whether this approach would be applicable in paralysed patients who are a target population for BCI remains an empirical question. (2) In some participants motor imagery lead to an enhancement of the SMR (event-related synchronization, ERS) compared to the measurement under the *relax* condition. In some of those cases the SMR predictor underestimated the performance, but these were few, see section '*Peri-Imagery ERS*'. (3) Some participants had a pronounced SMR which they managed to attenuate by motor imagery, but they were not able to sustain this attenuation long enough (i.e., until the end of the feedback trial), e.g., participants *lc* and *ky*. Those participants would have performed well if the feedback had been adapted to shorter trial durations. (4) The feedback runs started about 2.5 hours after the beginning of the experiment. This may have lead to problems in vigilance and may have degraded the feedback performance.

Possible Improvements of the SMR Predictor

Our observations indicated that the SMR predictor can be distorted by contributions from the occipital visual idling rhythm, which has a peak in the alpha frequency range and is typically much stronger than the SMR idling rhythm. Although the Laplacian filter over sensorimotor areas should cancel out contributions from the occipital site, this seemed not to be completely true in practice. To address the contribution of occipital alpha, we did the same analysis as above with segments acquired under the condition 'relax with eyes closed'- a condition know to substantially increase power in the alpha band over occipito-parietal areas. The results were substantially worse; namely, the correlation coefficient dropped from $r = 0.53$ to $r = 0.27$. But even with eyes open, the visual alpha rhythm does not disappear completely, and therefore it might deteriorate the predictive value of the SMR predictor. There are two approaches to counteract this potential problem. (1) The experimental paradigm can be changed such that there is a task which requires some visual processing during the 'relax' condition to suppress the visual alpha rhythm, e.g., watching a small abstract animation on the screen. (2) Spatial filters that are specifically designed for the positions C3 and C4 might be better in eliminating contributions from occipital sites than the Laplacians filters.

Conclusion

While some publications focus on reporting results for successful participants only, a percentage of 15-30% cases of BCI illiteracy are common in every BCI laboratory. So far, very little was known about possible reasons of such failures in BCI control. In the present study we found a reliable predictor of BCI performance: Two minutes of resting state EEG with eyes open measured at two Laplacian channels over left and right hand motor areas (positions C3 and C4) were sufficient to predict BCI performance during later feedback runs within the same BCI session.

Our results contribute to speed up studies that focus on SMR-based BCI based on a machine learning approach, because potentially non-successful subjects can be identified at the very beginning of a session. Further, our findings point at a versatile direction to counteract BCI illiteracy: In subjects who present with no SMR peak that could be modulated, operant conditioning procedures similar to [Birbaumer et al. (1999); Kübler et al. (2005); McFarland et al. (1998)] could be applied in a pre-training session to specifically enhance the power of the SMR idling rhythm. Future studies will therefore contrast and unite psychological shaping strategies with online machine learning approaches where the SMR is enhanced by individually optimized classification procedures.

Acknowledgements

This work was supported in part by grants of the *Deutsche Forschungsgemeinschaft* (DFG), MU 987/3-1 and KU 1453-1, *Bundesministerium für Bildung und Forschung* (BMBF), FKZ 01IB001A/B and 01GQ0850 and by the FP7-ICT Programme of the European Community, under the PASCAL2 Network of Excellence, ICT-216886. This publication only reflects the authors' views. Funding agencies are not liable for any use that may be made of the information contained herein.

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