Predicting BCI Performance to Study BCI Illiteracy

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Abstract. Brain-Computer Interfaces (BCIs) allow a user to control a computer application just by brain activity as acquired, e.g., by electroencephalography (EEG). After 30 years of BCI research, the success of BCI control that may be provided still greatly varies between subjects. For a percentage of about 20% the obtained accuracy does not reach the level criterion, meaning that BCI control is not accurate enough to control an application. The development of predictors of BCI performance serves two purposes: a better under-standing of the 'illiterates phenomenon', and avoidance of a costly and frustrating training procedure for subjects 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 subjects in their first session with the Berlin Brain-Computer Interface (BBCI) system which operates on modulations of sensory motor rhythms (SMRs).

Keywords: Brain-Computer Interface (BCI); Sensory Motor Rhythms (SMRs); Event-Related Desynchronization (ERD); Neurophysiological Predictor; BCI Illiteracy

1. Introduction

Amplitude modulations of sensorimotor rhythms (SMRs) can be voluntarily controlled by most subjects, e.g., by imagining movements. This ability can be taken as a basis for Brain-Computer Interfaces (BCIs) which are devices that translate the intent of a subject measured from brain signals directly into control commands, e.g., for a computer application or a neuroprosthesis ([Dornhege et al., 2007; Wolpaw et al., 2002; Kübler et al., 2001]).

Most SMR-based BCI systems require several training sessions in which subjects learn the ability to modulate their SMR appropriately to control a BCI application ([Vidaurre et al., 2006; Kübler et al., 2001]). Other approaches allow to provide BCI control already in the very first session, but still need a calibration period of about 30 minutes ([Blankertz et al., 2008a; Blankertz et al., 2007; Guger et al., 2000]). Additionally those systems typically use at least 60 electroencephalography (EEG) channels which require another 30 minutes of preparation with current sensor technology.

One of the biggest challenges in BCI research is to solve the problem of BCI illiteracy, which is that BCI control does not work for a non-negligible portion of subjects (estimated 15% to 30 %). In order to understand this phenomenon better, predictors of BCI performance are helpful to develop. Until the problem of 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 the possibility to use a BCI.

There exists some literature on predictors of performance with a BCI system based on the control of slow cortical potentials (SCPs) [Kübler et al., 2004]. Regarding SMR-based BCIs, to our knowledge [Burde and Blankertz, 2006] is the only approach to predict feedback performance. In that work a correlation of r = 0.59 was found between the psychological variable ‘locus of control by dealing with technology’ ([Beier 2004]) and BCI feedback performance in a group of $N = 17$ subjects.

2. Material and Methods

2.1. Neurophysiology

Macroscopic brain activity during resting wakefulness contains distinct ‘idle’ rhythms located over various brain areas, e.g., the parietal α-rhythm (8–12 Hz) can be measured over the occipital cortex. The perirolandic sensorimotor cortices show rhythmic macroscopic EEG oscillations (μ-rhythm), with spectral peak energies of about 9–14 Hz localized predominantly over the postcentral somatosensory cortex and typically phase synchronized components can be found in the beta band over the precentral motor cortex. Modulations of the μ-rhythm have been reported, e.g., for both actual and imagined movements ([Pfurtscheller and da Silva, 1999]). Standard trial averages of μ-rhythm power can reveal attenuation, termed event-related desynchronization (ERD, [Pfurtscheller and da Silva, 1999]), or increase (event-related synchronization, ERS). Typically, ERD is an indication of cortical activity, while ERS can be observed during cortical idling. Several EEG-based BCI systems rely on the fact that amplitude modulations of SMRs can be voluntarily controlled by most of the subjects, e.g., by imagining movements as explained above (see [Nikulin et al., 2008] for an interesting variation of the paradigm).

2.2. Experimental Setup

Eighty healthy BCI-novices (39m, 41f; age 29.9±11.5y; 4 left-handed) took part in this one-session study. The subjects were sitting in a comfortable chair with arms lying relaxed on armrests. Brain activity was recorded from the scalp with multi-channel EEG amplifiers using 119 Ag/AgCl electrodes in an extended 10-20 system sampled at 1000 Hz with a band-pass from 0.05 to 200 Hz. Additionally, we recorded electromyograms (EMG) from both forearms and the right leg as well as horizontal and vertical electrooculograms (EOG). The EMG channels were exclusively used to control for physical limb 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.

In the beginning, EEG was recorded while the subject performed ten periods of 15s with the alternating tasks to ‘relax with eyes open’ and to ‘relax with eyes closed’.

During the ‘calibration measurement’ every 8s one of three different visual cues (arrows pointing left, right, down) indicated to the subject which type of motor imagery to perform: left hand, right hand, or right foot. Three runs with 25 trials of each motor condition were recorded.

Then subjects performed in a ‘feedback measurement’ three runs of 100 trials each (for some subjects only one or two runs have been recorded due to fatigue or exhaustion).

2.3. BBCI Feedback

The EEG signals of the calibration measurement were bandpass-filtered in a subject-specific frequency band, temporally filtered in a subject-specific time interval (typically 750 to 3500 ms relative to the presentation of the visual cue), and spatially filtered with subject-optimized filters 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 results in a feature vector with dimensionality equal to the number of selected CSP filters. To our experience, those features can be well classified by linear methods and we used linear discriminant analysis (LDA).

For online operation, features were calculated every 40 ms from sliding windows of 750 ms width (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 fashion: At the beginning of each trial, the cursor started in the center of the screen and a fraction of the classifier output was added to the actual cursor position at each update step. The bias of the classifier was adapted on the first 20 trials of each feedback run ([Krauledat et al., 2008]). These trials have not been counted to calculate the feedback performance.

2.4. Performance Predictor

To determine the value of the proposed SMR predictor, only a short recording under the condition ‘relax with eyes open’ using two Laplacian channels (C3, C4) is required. For the present investigation, we used the concatenated segments of this condition from the artifact measurement, see Section 2.2.

From these data we calculate the power spectral density (PSD) in the Laplace-filtered channels C3, C4 and determine 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. Figure 1). These two values are estimates of the strength of the SMR over the hand areas. The SMR-predictor is the average of those two values. It quantifies the potential for desynchronization of the SMR.

For the fit, we model each PSD curve as a function g (say) of the frequency f with two additive components of the form

$$g(f; \lambda, \boldsymbol{\mu}, \boldsymbol{\sigma}, \mathbf{k}) = g_1(f; \lambda, \mathbf{k}) + g_2(f; \boldsymbol{\mu}, \boldsymbol{\sigma}, \mathbf{k}) \text{ with} \tag{1}$$

$$g_1(f; \lambda, \mathbf{k}) = k_1 + k_2 / f^{\lambda} \text{ and } g_2(f; \boldsymbol{\mu}, \boldsymbol{\sigma}, \mathbf{k}) = k_3\, \varphi(f; \mu_1, \sigma_1) + k_4\, \varphi(f; \mu_2, \sigma_2), \tag{2}$$

where $\mathbf{k}=(k_1,k_2,k_3,k_4)$ and λ are real numbers and $\varphi(\cdot; m, s)$ denotes the probability density function of a normal distribution with mean m and standard deviation s. Function g_1 is a model for the noise spectrum and function g_2 models the additional peaks in the PSD around α and β frequency ranges.

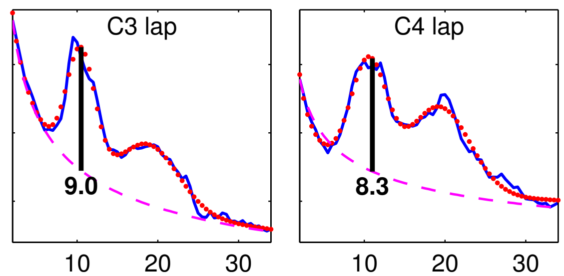

Figure 1. *Illustration of the calculation of the performance predictor. The plots show the spectra of a relax measurement (eyes open) of one subject for two Laplace-filtered channels over sensorimotor cortex (blue), the estimated noise floor $g_1(f; \lambda, \mathbf{k})$ (purple) and the fitted values $g(f; \lambda, \boldsymbol{\mu}, \boldsymbol{\sigma}, \mathbf{k})$ (red). In each channel the maximum elevation of the peaks above the noise floor is determined. The value of the SMR predictor is the average of these two values.*

As objective function for the optimization of the nine parameters (λ, $\boldsymbol{\mu} = (\mu_1,\mu_2)$, $\boldsymbol{\sigma} = (\sigma_1, \sigma_2)$, and $\mathbf{k}$) we choose the L_2-norm of the difference vector $PSD(\mathbf{f}) - g(\mathbf{f}; \lambda, \boldsymbol{\mu}, \boldsymbol{\sigma}, \mathbf{k})$, where $\mathbf{f}$ is the vector of all available frequency values for the PSD; in our case we have $\mathbf{f}$ = (2Hz,3Hz, . . . ,35Hz), see Figure 1. Since we decomposed the PSD into the noise component and the two peak components, the contribution of one channel to our proposed predictor is simply $\max_f g_2(f; \boldsymbol{\mu}, \boldsymbol{\sigma}, \mathbf{k}) \approx \max_f\{PSD(f) - \text{noise}(f)\}$.

3. Results

Feedback accuracy varied largely between subjects, covering the full range from chance-level performance (50%) to perfect control (100%). Performance also varied strongly between runs for most subjects. In Figure 2, the SMR-predictor is plotted against the performance in the feedback session. Despite of its simplicity, the SMR predictor obtains a Pearson correlation coefficient of $r = 0.53$, i.e., it explains as much as $r^2 = 28\%$ of the variance in feedback accuracy in our sample of $N = 80$ subjects.

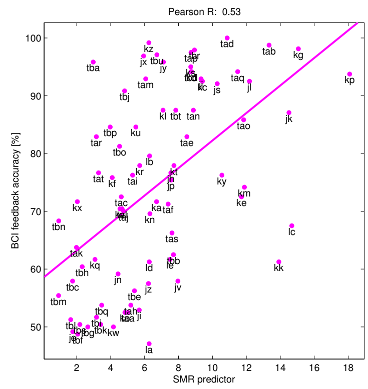

Figure 2. *Correlation of the SMR predictor with BCI feedback performance: Each dot corresponds to one subject (to be identified by a two or three letters subject code). Our proposed SMR predictor is plotted in horizontal direction against the BCI feedback performance in vertical direction. The solid line is the result of a linear regression analysis of the BCI feedback performance onto the SMR predictor. On top of the graph, the correlation coefficient according to Pearson between both entities is given.*

4. Discussion

Our performance predictor essentially estimates the amplitude of the SMR in order to estimate the potential for BCI performance assuming that motor imagery leads to an attenuation of the SMR ([Pfurtscheller and da Silva, 1999]). As shown, this approach leads to quite good prediction results, but there are several basic cases in which the SMR predictor fails. (1) Some subjects have a detectable SMR, but no class-specific attenuation of that rhythm. One possible reason for this phenomenon could be that these subjects used a wrong strategy, e.g., only visually imagining the movements instead of kinesthetically ([Neuper et al., 2005]). Subject *ji*, e.g., reported to have used abstract thoughts ("I rather thought *left* and *down"*) in the feedback instead of motor imagery as in the calibration measurement. For this subject 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 subjects who followed the instructions well. See [Nikulin et al., 2008] for an interesting approach to lead subjects to an effective strategy. (2) In some subjects motor imagery lead to an enhancement of the SMR (event-related synchronization, ERS) compared to the measurement under the *relax* condition. In these cases the SMR predictor underestimates the performance. (3) Some subjects 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., subjects *lc* and *ky*. Those subjects would perform well if the feedback were adapted to shorter trial durations. (4) Since additional measurements not related to this investigation have also been performed, feedback runs started about 2.5 hours after the beginning of the experiment. This fact might have led to problems in vigilance and might have degraded the feedback performance.

5. Conclusion

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. On the other hand, this insight may pave a way to approach the BCI illiteracy problem: further studies will evaluate a specifically tailored neurofeedback training in order to enhance the SMR idle rhythm and, as may be speculated, feedback performance in subsequent BCI applications. Nevertheless, a predictor for BCI performance explaining 28% of the variance is unique in the field of BCI.

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