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The Berlin Brain-Computer Interface: Report from the Feedback Sessions

Benjamin Blankertz*, Guido Dornhege, Matthias Krauledat, Klaus-Robert Müller, Gabriel Curio†

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Abstract

Brain-Computer Interface (BCI) systems establish a direct communication channel from the brain to an output device. These systems use brain signals recorded from the scalp, the surface of the cortex, or from inside the brain to enable users to control a variety of applications. BCI systems that bypass conventional motor output pathways of nerves and muscles can provide novel control options for paralyzed patients. The classical approach to establish EEG-based control is to set up a system that is controlled by a specific EEG feature which is known to be susceptible to conditioning and to let the subjects learn the voluntary control of that feature. In contrast, the Berlin Brain-Computer Interface (BBCI) uses well established motor competences in control paradigms and a machine learning approach to extract subject-specific discriminability patterns from high-dimensional features. Thus the long subject training is replaced by a short calibration measurement (20 minutes) and machine training (1 minute). We report results from a study with six subjects who had no or little experience with BCI feedback. The experiment encompassed three kinds of feedback that were all controlled by voluntary brain signals, independent from peripheral nervous system activity and without resorting to evoked potentials. Two of the feedback protocols were asynchronous and one was synchronous (i.e., commands can only be emitted synchronously with an external pace). The information transfer rate in the best session was above 35 bits per minute (bpm) for 3 subjects, above 24 and 15 bpm for further two subjects, while one subject could achieve no BCI control. Compared to other BCI systems which need longer subject training to achieve comparable results we believe that the key to success in the BBCI system is its flexibility due to complex features and its adaptivity which respects the enormous inter-subject variability.

1 Introduction

The aim of Brain-Computer Interface (BCI) research is to establish a new augmented communication system that translates human intentions—reflected by suitable brain signals—into a control signal for an output device such as a computer application or a neuroprosthesis [1]. According to the definition put forth at the first international meeting for BCI technology in 1999, a BCI “must not depend on the brain’s normal output pathways of peripheral nerves and muscles” [2].

There is a huge variety of BCI systems, see [1, 3, 4] for a broad overview. Our Berlin Brain-Computer Interface (BBCI) is a non-invasive, EEG-based system, which does not use evoked potentials. BCI systems relying on evoked potentials can typically achieve higher information transfer rates (ITRs) in contrast to systems working on unstimulated brain signals, cf. [5]. On the other hand with evoked potential BCIs the user is constantly confronted with stimuli, which could become exhaustive after longer usage.

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One of the major challenges in BCI research is the huge inter-subject variability with respect to patterns and characteristics of brain signals. In the operant conditioning variant of BCI, the subject has to learn self-control of a specific EEG feature which is hard-wired in the BCI system. An alternative approach tries to establish BCI control in the opposite way. While using much more general features the system automatically adapts to the specific brain signals of each user by using advanced techniques of machine learning and signal processing [6, 7, 8].

1.1 Earlier approaches

Other explorations of BCI systems were performed by the Graz BCI group as presented in [9, 10]. The former publication introduces the common spatial pattern (CSP) algorithm for the use in BCI systems, while the latter reports results from a feedback study with a CSP-based BCI operating on a 27 channel EEG. The feedback study encompassed 6 sessions on 4 days for each of three subjects that were experienced with BCI control. Nevertheless the result for two out of three subjects was at chance level in the first feedback session and reasonable BCI control was only obtained from the 2nd feedback session on. The feedback application did not allow to explore what information transfer rates could be obtained because it stuck to an synchronous design where each binary decision needed 8 s, limiting the highest possible ITR to 7.5 bits per minute (bpm) at a theoretical accuracy of 100 %. In a more recent publication ([11]) 4 patients with complete or partial paralysis or paresis of their lower limbs were trained to operate a variant of the Graz BCI that uses band power features of only 2 bipolar channels. As feedback application the basket game was used in which the subject controls the horizontal position of a ball that falls downward at constant speed. The aim is to hit one of two targets on the bottom of the screen. On the second and third day the maximum ITR of 6-16 runs of 40 trials each for the 4 subjects was between 3 and 17.2 bpm (mean 9.5±5.9).

A study from the Wadsworth BCI group ([12]) investigates the influence of trial duration and number of targets on the ITR in their BCI system that uses operant conditioning. 8 subjects (2 patients, one spinal injury at c6 and one cerebral palsy) trained over several month to operate a BCI application that is very similar to the basket game described above, but with vertical cursor control and a variable number of target fields. The average ITR from 8 runs of 20 to 30 trials for the 8 subjects was between 1.8 and 17 bpm (mean 8.5±4.7) at the individual best number of targets.

Based on offline results Millán et al. ([13]) suggests to use a simple local neural clasifier based on quadratic discriminant analysis for the machine learning part. Using this system in an online feedback asynchronously with three classes (left/right-hand motor imagery and relax with eyes closed) three subjects were able after a few days of training to achieve an averaged correct recognition of about 75 % whereas the wrong decision rate were below 5 %. In [14] it was reported that with this system a motorized wheelchair and a virtual keyboard could be controllted. In the latter case trained subjects were able to select a letter every 22 s. In a preliminary study the best subject was reported to be able to do it every 7 s. Note that brain signals for one class were produced by closing the eyes.

Here we report results of a study in which online feedback was provided by a CSP-based translation algorithm operating on a 120 channel EEG. Training and 3 feedback sessions have been conducted on one day for each of 6 subjects who had no or little experience with BCI control. Users could control 2 asynchronous feedback application for binary decisions and 1 synchronous feedback application for ternary decisions at a comparably high speed: The mean decision speed was between 2.5 and 3 s for each of the three feedback scenarios.

The information transfer rate in the best feedback session for each subject was above 15 bits per minute (bpm) for five of six subjects. Three subjects achieved even bit rates above 35 bpm. The possibility that the BCI control is based on concurrent EMG activity can be excluded by inspection of EMG signals that have be measured for this purpose. The fact that the BBCI works without being dependent on eye movements or visual input in any way was verified by letting two subjects control the BBCI with eyes closed which worked comparably well as in the closed loop feedback.

2 Neurophysiology and Features

According to the 'homunculus' model, first described in [15], for each part of the human body exists a corresponding region in the primary motor and primary somatosensory area of the neocortex. The 'mapping' from the body part to the respective brain areas approximately preserves topography, i.e., neighboring parts of the body are represented in neighboring parts of the cortex. For example, while the feet are located close to the vertex, the left hand is represented lateralized (by about 6 cm from the midline) on the right hemisphere and the right hand almost symmetrically on the left hemisphere.

Macroscopic brain activity during resting wakefulness contains distinct 'idle' rhythms located over various brain areas, e.g., the μ-rhythm can be measured over the pericentral sensorimotor cortices in the scalp EEG, usually with a frequency of about 10 Hz ([16]). Furthermore, in electrocorticographic recordings Jasper and Penfield ([15]) described a strictly local beta-rhythm at about 20 Hz over the human motor cortex. In non-invasive scalp EEG recordings the 10 Hz μ-rhythm is commonly mixed with the 20 Hz-activity. Basically, these rhythms are cortically generated; while the involvement of a thalamo-cortical pacemaker has been discussed since the first description of EEG by Berger ([17]), Lopes da Silva ([18]) showed that cortico-cortical coherence is larger than thalamo-cortical pointing to a convergence of subcortical and cortical inputs.

The moment-to-moment amplitude fluctuations of these local rhythms reflect variable functional states of the underlying neuronal cortical networks and can be used for brain-computer interfacing. Specifically, the pericentral μ- and beta rythms are diminished, or even almost completely blocked, by movements of the somatotopically corresponding body part, independent of their active, passive or reflexive origin. Blocking effects are visible bilateral but with a clear predominance contalateral to the moved limb. This attenuation of brain rhythms is termed event-related desynchronization (ERD), see [19].

Since a focal ERD can be observed over the motor and/or sensory cortex even when a subject is only imagining a movement or sensation in the specific limb, this feature can well be used for BCI control: The discrimination of the imagination of movements of left hand vs. right hand vs. foot can be based on the somatotopic arrangement of the attenuation of the μ and/or β rhythms. To this end, different ways to improve the classification performance of the CSP algorithm were suggested, e.g., [20], but evaluated only in offline studies so far.

A complementary EEG feature reflecting imagined or intended movements is the lateralized Bereitschaftspotential (LRP), a negative shift of the DC-EEG over the activated part of the primary motor cortex ([21]). The LRP feature was used in combination with colocalized ERD features and showed very encouraging results in offline BCI classification studies [22, 23].

3 Experimental Setup

Six subjects (all male; 1 left handed; age 27–46 years) took part in a series of feedback experiments with one fixed setup. None of the subjects had extensive training with BCI feedback: Two subjects had one session with an earlier version of BBCI feedback, one subject had one and two subjects had four sessions of BBCI feedback before. One subject had no prior experience with BCI feedback.

Brain activity was recorded with multi-channel EEG amplifiers using 128 channels band-pass filtered between 0.05 and 200 Hz and sampled at 1000 Hz. For all results in this paper, the signals were subsampled at 100 Hz. Additionally surface EMG at both forearms and the right leg, as well as horizontal and vertical EOG signals, were recorded. Those signals were only measured in order to check the absense of target related muscle activity or eye movements, *not* for generating the feedback. Subjects sat in a comfortable chair with arms placed on armrests.

3.1 Training Sessions

All experiments contain a so called training sessions in which the subjects performed mental motor imagery tasks according to visual stimuli. In such a way labeled examples of brain activity can be obtained during the different mental tasks. These recorded single trials were then used to train a classifier by machine learning techniques which was applied online in the feedback sessions to produce a feedback signal for (unlabeled) continuous brain activity. Note that the 'training sessions' are only used to generate examples to *train the classifier*, not to *train the subject*.

In the training session visual stimuli indicated which of the following 3 motor imageries the subject should perform: (L) *left* hand, (R) *right* hand, or (F) right *foot*. The presentation of target cues were intermitted by periods of random length, 1.75 to 2.25 s, in which the subject could relax.

There were two types of visual stimulation: (1) where targets were indicated by letters appearing behind a fixation cross and (2) where a randomly moving object indicated targets. Since the movement of the object was independent from the indicated targets target-uncorrelated eye movements are induced. From 3 subjects 2 sessions of both types were recorded, while from the other 3 subjects 1 session of type (1) and 3 sessions of type (2) were recorded.

3.2 Feedback Sessions

After the training sessions were recorded the experimentor investigated the data to adjust subject-specific parameters of the data processing methods, see Sec. 4.3 and Sec. 5.2. Then he identified the two classes that gave best discrimination and trained a binary classifier as described in Sec. 4. The third class was not used for feedback. In cases where the cross-validation (cf. Sec. 5.1) predicted a reasonable performance, the subject continued with three kinds of feedback sessions. The first two have an asynchronous protocol, while the last is synchronous. Since most timing details were individually adapted for each subject, we will here only state the range in which those changes occurred. In all feedback scenarios, we arranged the display according to the selected paradigms, in particular we wanted to make the movement most intuitive for the subjects. If the selected classes were "right hand" and "right foot", then a vertical movement was more intuitive than a horizontal one. For reasons of legibility, only the setup for the horizontal movement will be described in the following sections.

3.2.1 1D 'absolute' Cursor Control

The first type of feedback presented to the subjects consisted of the control of a cursor in one-dimensional (i.e., horizontal) direction. Items on the screen included the cursor in form of a red cross of approx. 3 cm width, two targets in form of grey rectangles of 15 cm height and 3 cm width (one at each side of the screen) and a counter at the top left corner of the screen, indicating the respective numbers of successful and unsuccessful trials. In the middle, a light gray rectangle of 20 cm width denoted a designated central area, see 1.

The display was refreshed at 25 fps, and with every new frame at point t_0, the cursor was updated to a new position $(p_{t_0}, 0)$ calculated from the classifier output $(cl_t)_{t<=t_0}$, according to the formula

$$p_{t_0} = s(\frac{1}{n} \sum_{t=t_0-n+1}^{t_0} cl_t - b),$$

where scaling factor s, bias b and averaging length n were manually adjusted during a calibration session. We then restrict the range of the above expression to the interval $[-1, 1]$ and translated this interval to horizontal positions on the screen.

At the beginning of each trial, the cursor was inactive (indicated by a black dot), but was already controlable by the subject. In this phase, no target could be selected, until the cursor was directed into the central area of the screen. 100–500 ms after the last hit, one randomly selected target was highlighted in

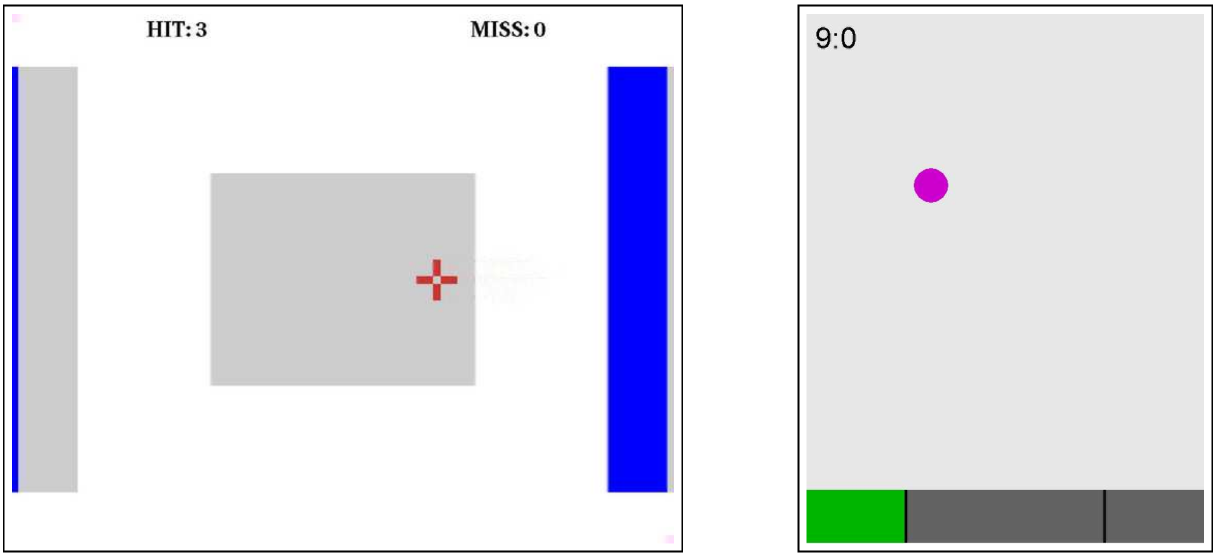

Figure 1: The setup of the feedback session. Left panel - "cursor control": In this situation, the cursor is active and the right rectangle is marked as the current target. The stripe on the left side indicates that after the current target, the left rectangle will be highlighted. Right panel: – "basket game": The subject controls the horizontal position of a ball that falls downward at constant speed. The aim is to hit one of two targets on the bottom of the screen.

blue. The task for the subject consisted now of steering the activated cursor into this target by imagining the corresponding movements, see Sec. 3.2 and 3.2. Once a target was hit by the cursor, the target was colored green (or red) to show the success (or failure) of the task, and the cursor was deactivated again. The deactivation of the cursor after the trial prevented multiple activations of the same target. As an additional orientation for the subjects, a 1 cm stripe at the outmost section of the targets was colored blue or gray to indicate if or if not this side was going to be the next target after the current one. Each run consisted of 25 trials of this kind.

3.2.2 1D 'relative' Cursor Control

The setup for the second type of feedback was similar to the previous one, only the control strategy for the cursor was slightly modified. In this setting, the cursor was moving in a "relative" fashion, meaning that with every new frame, the new position p_{t_0} was the old position p_{t_0-1}, shifted by an amount proportional to the classifier output:

$$p_{t_0} = p_{t_0-1} + s\left(\frac{1}{n}\sum_{t=t_0-n+1}^{t_0} cl_t - b\right).$$

In other words, in this setting, the first derivative (i.e., direction and speed) of the cursor position was controlled rather than its absolute position.

After each trial, the cursor was reset to the central position and was kept fixed for 750–1000 ms. Accordingly, the deactivation of the cursor could be skipped in this setup.

3.2.3 Basket Game

Here the scene consisted of three targets, gray rectangles at the bottom of the screen of approx. 3 cm height, and a counter at the upper left of the screen, which showed the number of successful and unsuccessful trials. The two outer rectangles were smaller than the middle one to account for the fact that they were easier to hit. In each trial, one of the targets was highlighted in blue, and the subject was trying to direct a cursor in the form of a magenta ball into this target. The cursor appeared at the top of the screen and was held there for 500–750 ms. Then it was moving down at a fixed rate such that it reached the bottom 1200–3000 ms after its release. The subjects were able to control the horizontal position of the cursor in a similar fashion to the cursor control strategies mentioned above. In this manner, they could try to hit the intended target when the cursor reached the bottom line. After the completion of a trial, the target was highlighted green or red, according to the success of the trial. The next trial began 250 ms after hitting the target.

This feedback was similar to those described in [12, 11], cf. Sec. 1, but here, as mentioned above, we changed the sizes of the targets according to the difficulty to reach them.

3.2.4 Manual calibration

In our very first feedback experiments we realized that the initial classifier was behaving suboptimal. Thus we introduced a calibration phase at the beginning of the feedback sessions in which the subject controlled the cursor freely and the experimentor adjusted the bias and the scaling of the classifier. Our investigations show that this adjustment is needed to account for the different experimental and mental conditions of the more demanding feedback situation when compared to the training session.

4 Methods

Machine learning techniques allow to learn from training data parameters as (spatial and spectral) filter coefficients, separation of the class distributions, and hyperparameters of all involved methods which are needed for the online translation algorithm. Often some of the hyperparameters are either set to default values or selected manually. In this section we give the broad picture of these two processes: (1) learning from training data, and (2) translating online brain signals to a control signal, see Sec. 5 for details. For completeness we also summarize the Common Spatial Pattern Algorithm.

4.1 Common Spatial Pattern (CSP) Analysis

The common spatial pattern (CSP) algorithm [24] is highly successful in calculating spatial filters for detecting ERD/ERS effects [25] and for ERD-based BCIs, see [9] and has been extended to multi-class problems in [22]. Given two distributions in a high-dimensional space, the CSP algorithm finds directions (i.e., spatial filters) that maximize variance for one class and that at the same time minimize variance for the other class. After having bandpass filtered the EEG signals in the frequency domain of interest, high or low signal variance reflect a strong respective a weak (attenuated) rhythmic activity. Let us take the example of discriminating left hand vs. right hand imagery. According to Sec. 2, if the EEG is first preprocessed in order to focus on the μ and β band, i.e. bandpass filtered in the frequency range 7–30 Hz, then a signal projected by a spatial filter focussing on the left hand area is characterized by a strong motor rhythm during the imagination of right hand movements (left hand is in idle state), and by an attenuated motor rhythm if movement of the left hand is imagined. This can be seen as a simplified exemplary solution of the optimization criterion of the CSP algorithm: maximizing variance for the class of right hand trials and at the same time minimizing variance for left hand trials. Furthermore the CSP algorithms calculates the dual filter that will focus on the area of the right hand (and it will even calculate several filters for both optimizations by considering orthogonal subspaces).

To be more precise, let $\boldsymbol{X}^k = \left(X^k_{c,t}\right),\ c = 1, \ldots, C,\ t = t_0, \ldots, T$ denote the (potentially bandpass filtered) EEG recording of the k-th trial, where C is the number of electrodes. Correspondingly $Y^k \in \{1;2\}$ represents the class-label of the k-th trial. Using this notation then the two class-covariance matrices are given as,

$$\Sigma_l = \langle \boldsymbol{X}^k {\boldsymbol{X}^k}^\top \rangle_{\{k: Y^k = l\}}, \quad l \in \{1;2\}. \tag{1}$$

The CSP analysis consists in calculating a matrix W and diagonal matrix D with elements in $[0, 1]$ such that

$$W\Sigma_1 W^\top = D \qquad \text{and} \qquad W\Sigma_2 W^\top = I - D. \tag{2}$$

This can be accomplished in the following way. First *whiten* the matrix $\Sigma_1 + \Sigma_2$, i.e., determine a matrix P such that

$$P(\Sigma_1 + \Sigma_2)P^\top = I. \tag{3}$$

This decomposition can always be found due to positive definiteness of $\Sigma_1 + \Sigma_2$. Then define $S_l = P\Sigma_l P^\top, l \in \{1, 2\}$ and calculate an orthogonal matrix R and a diagonal matrix D by spectral theory such that

$$S_1{}^\top = RDR^\top. \tag{4}$$

From $S_1 + S_2 = I$ it follows that $S_2{}^\top = R(I - D)R^\top$. Note that the projection given by the p-th row of matrix R has a relative variance of d_p (p-th element of D) for trials of class 1 and relative variance $1 - d_p$ for trials of class 2. If d_p is close to 1 the filter given by the p-th row of R maximizes variance for class 1, and since $1 - d_p$ is close to 0, minimizes variance for class 2. The final decomposition, that satisfies Eq.(2) can be obtained from,

$$W := R^\top P. \tag{5}$$

Using this decomposition matrix W the EEG recordings $\boldsymbol{X}^k$ are projected onto

$$\boldsymbol{Z}^k = W\boldsymbol{X}^k. \tag{6}$$

The interpretation of W is two-fold, the rows of W are the stationary spatial filters, whereas the columns of W^{-1} can be seen as the common spatial patterns or the time-invariant EEG source distribution vectors.

Thus, the latter can be used to verify neurophysiological plausibility of the calculated solution, while the former typically incorporate an intricate weighting which is needed to project out artifacts and noise sources and to optimize discriminability, see Fig. 2. Recently interesting extensions of CSP for multiclass settings as well as optimized spatio-temporal filter extensions of CSP have been proposed [22, 20].

4.2 Classification with LDA

The linear discriminant analysis (LDA) is obtained by deriving the classifier that minimizes the risk of misclassification under the assumption that the class distributions obey known gaussian distributions with equal covariances. Denoting the common covariance matrix by Σ and the class means by μ_l ($l = 1, 2$) the decision function of LDA is given by

$$x \mapsto 1.5 + 0.5 * (w^\top(x - \frac{1}{2}(\mu_1 + \mu_2))),$$

where $w = \Sigma^{-1}(\mu_2 - \mu_1)$.

4.3 Learning from Training Data

The basic idea is to extract spatial filters that optimize the discriminability of multi-channel brain signals based on event-related desynchronization effects of the (sensori-) motor rhythms, then to calculate the band energy in those surrogate channels and finally to find a separation of the two classes (mental states) in the feature space of those band energy values. This process involves several parameters that are individually chosen for each subject, as described in Sec. 5.2. Such parameters are indicated by variable names typeset in typewriter font.

1. From the three available classes, only event markers of the two classes with better discriminability are retained.

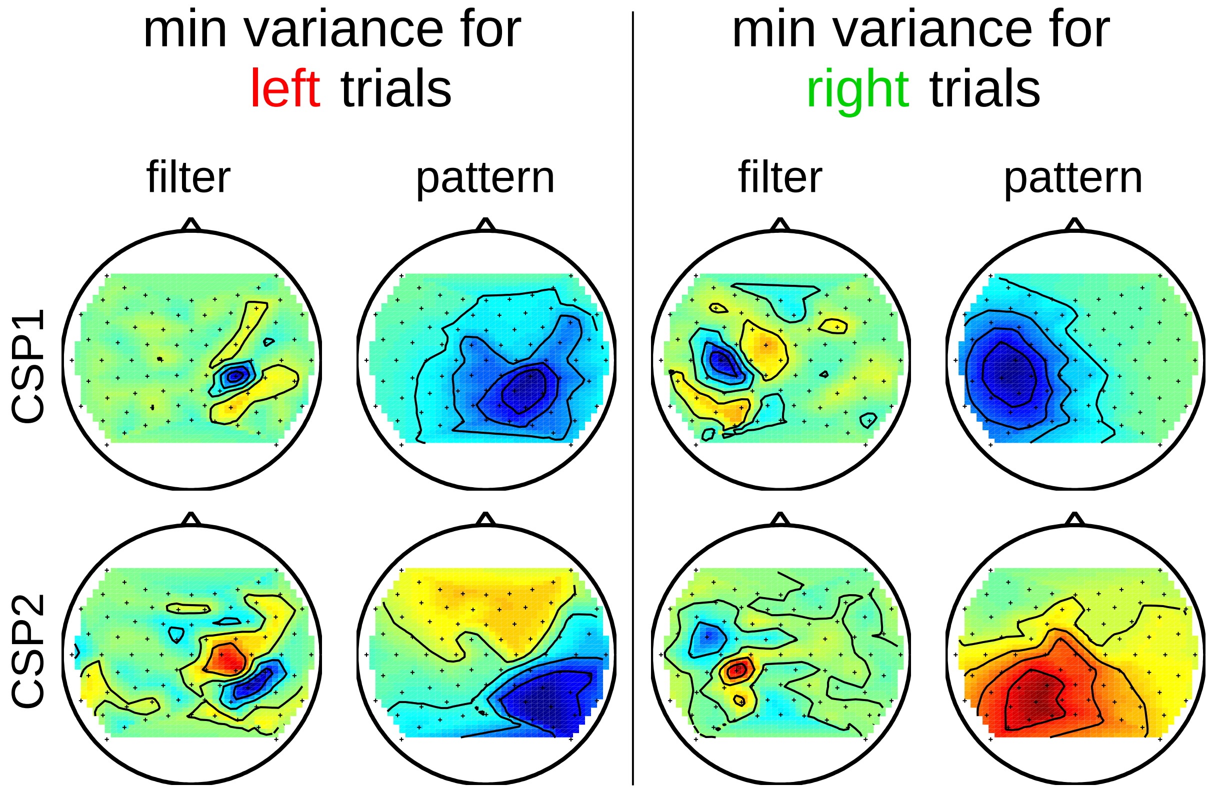

Figure 2: The common spatial pattern (CSP) algorithm determines spatial structures which represent the optimal discrimination between two classes with respect to variance. The patterns illustrate how the presumed sources project to the scalp. They can be used to verify neurophysiological plausibility. The filters are used to project the original signals. They resemble the patterns but their intricate weighting is essential to obtain signals that are optimally discriminative with respect to variance. Here two filters (resp. patterns) per class are shown (CSP1 and CSP2).

2. The raw EEG time series are band-pass filtered with a butterworth IIR filter of order 5 with passband `band`.
3. Trials are constructed from the filtered EEG signals for each event marker representing the interval `ival` relative to the time point of visual cues (marker position).
4. CSP is used to find 3 spatial filters per class by applying the algorithm to the trials classwise concatenated along time. From those 6 filters some were potentially dropped according to the neurophysiological plausibility of the corresponding patterns.
5. Variance was calculated for each of the CSP channels and the logarithm was applied to yield a feature vector for each trial.
6. The LDA classifier was used to find a separation between the mental states. Note that this classification process can in principle be enhanced by using more complex classifiers [7].

4.4 Online Translation Algorithm

In the online application a new feedback output was calculated every 40 ms (resp. 4 sample points) per channel. The continuously incoming EEG signals were processed as follows:

1. The EEG channels were spatially filtered with the CSP projection matrix that was determined from the training data. The result were 3 to 6 channels, depending on how many CSP filters were chosen.
2. The 4 new data points per channel were spectrally filtered with the chosen band-pass filter. The initial conditions of the delay for the filter are set to the final conditions of the filtering of the previous block of data.
3. From the last `ilen_apply` ms of data the variance was calculated in each (new) channel and the logarithm was applied.
4. Feature vectors are projected perpendicular to the separating hyperplane of the LDA classifier.
5. The classifier output is scaled and a bias is added.
6. Several consecutive outputs (`integrate`) are averaged.

Note that the ordering of spectral and spatial filtering was changed from the training to the apply phase. This is possible due to the linearity of those operations and considerably reduces computing time, since the number of channels that are to be filter are reduced from about 100 (original EEG channels) to at most 6 (CSP channels).

5 Methodological and Technical Details

5.1 Validation

A validation was used to estimate the generalization error of the classifier trained on the data of the training sessions. To this end we used a 3 times 5-fold cross-validation, i.e., for 3 repetitions all samples were partitioned into 5 parts, each of which was used as test set once, while the other 4 were used for training. Thus, 15 test set errors were determined and averaged. Since the CSP algorithm uses class label information, the calculation of the CSP filters has to be performed *within* the cross-validation on samples of the respective training set and the spatial filters are applied to the samples of the test set. That means for a 3 times 5-fold cross-validation the CSP algorithm is executed 15 times.

5.2 Selection of Parameters in the Training Procedure

The selection of the parameters of the training procedure, cf. Sec. 4.3 was done semiautomatically based on class-wise averaged plots of the spectra (parameter `band`, default [7 30]), of the ERD curves (parameter `ival`, default [750 4000]) and of the respective r^2-values. (The r^2-coefficient reflects how much of the variance in the distribution of all samples is explained by the class affiliation. It is the squared bi-serial correlation coefficient r:

$$X_r := \frac{\sqrt{N^+ \cdot N^-}}{N^+ + N^-} \frac{\mathrm{mean}(X^-) - \mathrm{mean}(X^+)}{\mathrm{std}(X^+ \cup X^-)}, \quad X_{r^2} := X_r^2$$

where X^+ and X^- are the samples of class 1 and 2 respectively, and N^+ and N^- are the numbers of samples.) Additionally the generalization error, cf. Sec. 5.1, was used as indicator for good parameter values. Choosing the pair of classes to be used for feedback was mainly based on comparing the cross-validation errors, but in debatable cases also the subject was asked what he would rather use for control paradigm. The outcome of the CSP analysis (3 patterns and filters per class) is visualized as in Fig. 2 and is used to decide which CSP filters are to be used and which are to be dropped.

5.3 Selection of Parameters in the Feedback Application

At the very beginning of the feedback sessions an exploratory phase "cursor control absolute" was performed during which experimenter and subject found out interactively which values for the parameters of the feedback application were most convenient for the subject. In the first step the bias and the scaling of the classifier were fine tuned. The values for the parameter `ilen_apply` was typically chosen between 500 and 1000 ms and the value for `integrate` was left at the default value 8. Subject 4 wanted to have a more immediate feedback and chose 300 ms and 5. For the basket feedback, subjects could choose how fast the ball was falling down.

6 Results of the Feedback Sessions

For two subjects the combination *left* vs. *right* was chosen, for two other subjects *left* vs. *foot* and for the remaining subject *right* vs. *foot*.

Each feedback session consisted of several runs with 25 targets each. Two successive runs were interrupted by a short break. The number of runs performed were different for each subject and feedback. The subjects performed 6 to 8 runs of absolute cursor control, 8 runs of relative cursor control and between 4 and 9 runs of the basket game. As a performance measure Wolpaw et al ([2]) suggests a value, called information transfer rate, based on information theory: The interface is described by a communication channel with noise (classification error) where the transmitter (the human) has to add redundancy such that a received decision can be achieved with an arbitrarily small probability of errors. With the confusion matrix $P = (p_{i,j})_{i,j=1,\ldots,N}$ ($p_{i,j}$ describes the probability to achieve at j if decision i was desired) the formula for the ITR per decision is given by $I_d = \log_2 N + \frac{1}{N}\sum_{i,j} p_{i,j} \log_2 p_{i,j}$. Consequently the ITR per time is defined by $I := f I_d$ with f as decision rate. For simplification we assume that $p_{i,i} = p$ and $p_{i,j} = \frac{1-p}{N-1}$ for all i, j. Then we get $I_d = \log_2 N + p \log_2 p + (1-p) \log_2 \frac{1-p}{N-1}$. Note that the assumption $p_{ij} = p_{ji} (i \neq j)$ is problematic for the basket feedback, since neighboring targets are more likely to be accidentally hit. However, an estimation of the confusion matrix based on the given basket feedback data is too imprecise such that we prefer to use the simplification with a more robust estimation of the classification accuracy. Table 1 summerizes the information transfer rates that were obtained by the 5 subjects in the three feedback sessions. Highest ITRs were obtained in the 1D 'relative' cursor control scenario.

One point that is to our knowledge special about the BBCI is that it can be operated at a high decision speed, not only theoretically, but also in practice. In the absolute cursor control the total trial

Table 1: Information transfer rates (ITR) obtained in the feedback sessions measured in bits per minute as obtained by Shannon's formula. For each feedback session the first column reports the average ITR of all runs, while the second column reports the peak ITR of all runs. Subject 2 did not achieve BCI control.

	training	**cursor abs**		**cursor rel**		**basket**	
	acc [%]	overall	peak	overall	peak	overall	peak
1	95.4	7.1	15.1	5.9	11.0	2.6	5.5
2	64.6	–	–	–	–	–	–
3	98.0	12.7	20.3	24.4	35.4	9.6	16.1
4	78.2	8.9	15.5	17.4	37.1	6.6	9.7
5	78.1	7.9	13.1	9.0	24.5	6.0	8.8
6	97.6	13.4	21.1	22.6	31.5	16.4	35.0
mean	85.3	10.0	17.0	15.9	27.9	8.2	15.0

length was 3 seconds, in relative cursor control 2.5 seconds. In the basket feedback the trial length is constant (synchronous protocol) but was individually selected by each subject, ranging from 2.1 s to 3 s. The fastest subject was no. 4 which performed at an average speed of one decision every 1.7 s in relative cursor control. The most reliable performance was achieved by subject 3: only 2% of the total 200 trials in the relative cursor control were misclassified at an average speed of one decision per 2.1 s.

7 Performance Predictor

In the presented setup it is somewhat time consuming to come to the point where the classifier can be trained and evaluated in order to see whether the performance is good enough for switching to online feedback (preparation of 128 channels, record 20 to 30 minutes of training data). Thus it is highly desirable to have a BCI performance predictor that can easily and quickly be consulted. The idea presented in the following is quite simple but nevertheless it works surprisingly well.

In the presented setup the BBCI is controlled by the desynchronization of the μ-rhythm. Typically BCI control fails only when no sensorimotor rhythms can be measured in scalp EEG. We observed also cases where subjects have a detectable μ-rhythm, but no class-specific modulation can be observed. In such cases it is likely that the subject used a wrong strategy, e.g., only visually imagining the movements instead of sensually. Our performance predictor essentially estimates the signal strength of the μ rhythm in order to detect the first kind of BCI failure subjects. To this end we measure EEG for one minute under a relax condition with eyes open.

From these data we calculate the power spectral density in the bipolar channels FC3-CP3, FCz-CPz, FC4-CP4 and determine for each of those channels the area under the curve of the peak in the 10 Hz range, see Fig. 3. These three values are estimates for the amplitude of the μ-rhythm over the areas of the right hand, foot, and left hand. The μ-indicator is the average of those three values.

In Fig. 4 the μ-indicator is plotted against the performance in the training resp. feedback session. For the latter we have taken the performance of the best session of absolute cursor control. Obviously the μ-indicator can only be a limited predictor for the accuracy of the BCI performance. Nevertheless in view of its simplicity the correlation of the μ-indicator with the BCI performance is surprisingly good. The main point of such an indicator would be that it indicates whether for a subject the probability of successful BCI control is very low such that in those cases the effort can be skipped (or the subject is switched to another BCI system, not relying on ERD of sensorimotor rhythms). The presented setup requires the montage of three bipolar EEG channels and an EEG measurement of 1 minute.

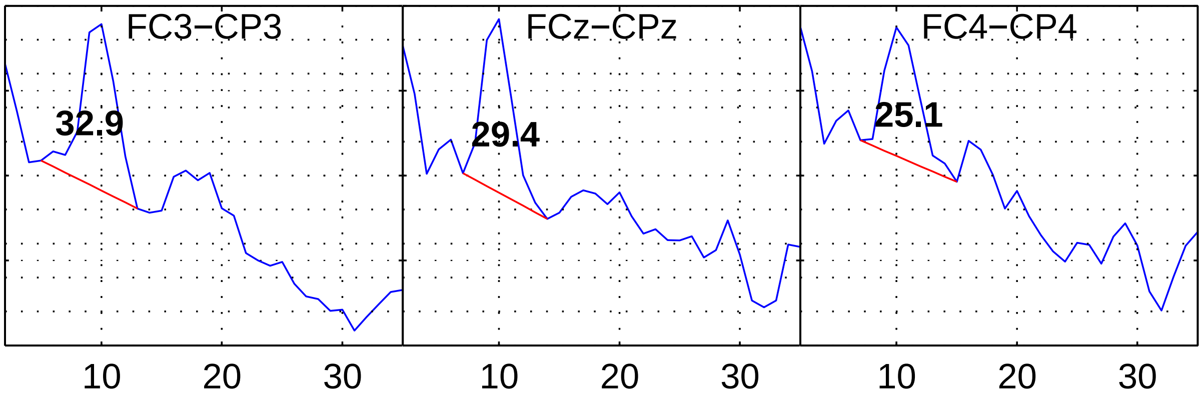

Figure 3: Illustration of the calculation of the performance predictor. The plots show the spectra of a relax measurement (eyes open) of one subject for three bipolar channels over sensorimotor cortex.

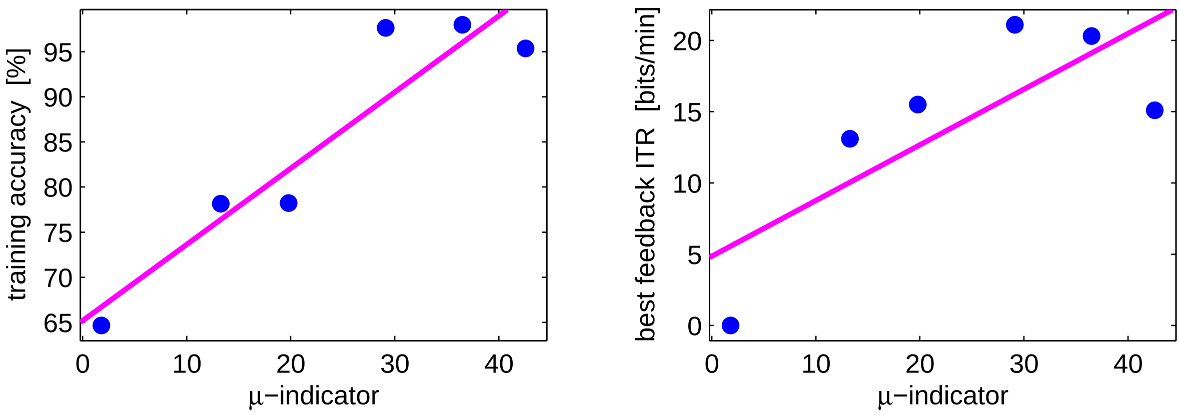

Figure 4: Left panel: Performance indicator vs. classifier accuracy (100 - generalization error) on the training data. Right Panel: Performance indicator vs. information transfer rate (ITR) in the feedback session with absolute cursor control.

8 Discussion and Outlook

The Berlin Brain-Computer Interface project makes use of a machine learning approach towards BCI. Working with high dimensional, complex featues obtained from 128 channel EEG allows the system a distinct flexibility for adapting to the specific individual characteristics of each user's brain. The result from a feedback study with six subjects impressively demonstrates that our system (1) robustly transfers the discrimination of mental states from the training to the feedback sessions, (2) allows a very fast switching between mental states, (3) provides reliable feedback directly after a short calibration measurement and machine training without the need that the subject adapts to the system (all at high information transfer rates, see table 1).

Additionally we presented a simple but highly efficient approach for obtaining a μ-indicator that allows to approximately predict the BCI performance from a one minute recording with 3 bipolar channels.

Recent BBCI activities comprise (a) mental typewriter experiments, where we have integrated a detector for the Error Potential, (b) the online use of combined feature and multi-class paradigms and (c) general real-time single-trial EEG analysis in more natural paradigms, e.g. in driving situations.

Our future studies will strive for 2D cursor control and robot arm control, still maintaining our philosophy of minimal subject training.

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