The Berlin Brain-Computer Interface: EEG-based communication without subject training

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***Abstract*— The Berlin Brain-Computer Interface (BBCI) project develops a non-invasive BCI system whose key features are (1) the use of well-established motor competences as control paradigms, (2) high-dimensional features from 128-channel EEG and (3) advanced machine learning techniques. As reported earlier, our experiments demonstrate that very high information transfer rates can be achieved using the readiness potential (RP) when predicting the laterality of upcoming left vs. right hand movements in healthy subjects. A more recent study showed that the RP similarily accompanies phantom movements in arm amputees, but the signal strength decreases with longer loss of the limb. In a complementary approach oscillatory features are used to discriminate imagined movements (left hand vs. right hand vs. foot). In a recent feedback study with 6 healthy subjects with no or very little experience with BCI control, 3 subjects achieved an information transfer rate above 35 bits per minute (bpm), and further two subjects above 24 and 15 bpm, while one subject could not achieve any BCI control. These results are encouraging for an EEG-based BCI system in untrained subjects that is independent of peripheral nervous system activity and does not rely on evoked potentials even when compared to results with very well-trained subjects operating other BCI systems.**

***Index Terms*— Brain-Computer Interface, Classification, Common Spatial Patterns, EEG, ERD, Event-Related Desynchronization, Information Transfer Rate, Readiness Potential, RP, Machine Learning, Single-Trial Analysis**

I. 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]. This viewpoint is certainly for research purpose in order to have clear evidence of what information a systems uses and where it comes from. Nevertheless there seems to be consensus in the BCI community that in specific BCI applications (e.g., for paralyzed patients) it may be reasonable to get all signals that provide useful information regardless of their origin.

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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 can become exhaustive after longer usage.

Here we present two aspects of the main approach taken in the BBCI project. The first is based on the discriminability of premovement potentials in self-paced movements. Our initial studies ([6]) show that high information transfer rates can be obtained from single-trial classification of fast-paced motor commands. Additional investigations point out ways of improving bit rates further, e.g., by extending the class of detectable movement related brain signals to the ones encountered when moving single fingers within one hand. A more recent study showed that it is indeed possible to transfer the results obtained with regard to movement intentions in healthy subjects to phantom movements in patients with traumatic amputations.

Taking another approach, we established a BCI system based on motor imagery that works without subject training. Using general, complex features derived from 128-channel EEG recordings the system automatically adapts to the specific brain signals of each user by using advanced techniques of machine learning and signal processing [7], [8], [9]. This approach contrasts with the operant conditioning variant of BCI, in which the subject has to learn to control a specific EEG feature which is hard-wired in the BCI system. According to the motto 'let the machines learn' our approach minimizes the need for subject training and copes with one of the major challenges in BCI research: the huge inter-subject variability with respect to patterns and characteristics of brain signals.

II. Approach 1: Self-paced and Phantom Finger Movements

A. Exploiting the limits of the refractory behavior in fast-paced motor commands

The main goal of BCI is to improve autonomy of people with severe motor disabilities by new communication and control options. These persons cannot move but can think about moving their limbs and produce in this way stable motor-related signals like the readiness potential (RP, or Bereitschaftspotential, BP) and event-related desyncronization (ERD). The RP is a transient postsynaptic response of main pyramidal peri-central neurons, see [10]. It leads to a negativation of the EEG over primary motor cortices during motor preparation that peaks about movement onset. In hand movements it is focused contralateral to the performing hand, cf. [11], [12] and references therein for an overview. The preparation of movements is reflected also by an ERD, i.e., an attenuation of pericentral μ- and β-rhythms in the corresponding motor areas. With respect to unilateral hand movements these blocking effects are visible bilateral but with a clear predominance contalateral to the performing hand, cf. [13]. In controls, imagined movements produce motor related signals ([14]), but less pronounced in comparison to executed movements probably owing to duality of the task of imagining a movement but at the same time vetoing the actual movement. Therefore a real movement made by a healthy subject is more like the motor-command in disabled persons than an imagined movement. Our main interest in the following experiment was the examination of *stability and refractory behavior of motor related brain signals* with increasing speed of execution and the associated bit-rate.

For this reason we examined the cortical signals of executed finger movements in experimental settings with different movement speeds. We started a series of experiments with healthy volunteers performing self-paced finger-movements on a computer keyboard with approximate tap-rates of 30, 60 and 120 keystrokes per minute (kpm). EEG was recorded from 64 Ag/AgCl scalp electrodes. Electromyogram (EMG) was obtained from *M. flexor digitorum communis* from both sides to detect EMG onset. EEG was segmented, averaged and baseline-corrected in the case of RP. In case of ERD/ERS we first determined the individual power-peaks in the μ frequency range from power spectral density plots and chose subject-specific band-pass filters accordingly. The lower limit was in every case between 7 and 9 Hz and upper bound was 13 or 14 Hz. After band-pass filtering, signals were Laplace-transformed, rectified, segmented, class-wise averaged and smoothed. Fig. 1 shows averaged data from the two subjects (VP 1 and VP 2), RPs for the first and ERDs for the second. One can see for RP from VP 1 predominantly contralateral negativation before EMG-onset (which is 120 ms before keypress) and regeneration after movement. In contrast to the behavior of the RP a different kind of activation/deactivation behavior could be seen in the μ-bandpass filtered data. Most prominent in the preparatory phase of the movement is the ipsilateral synchronization along with a slide contralateral desynchronization. In the single-trial classification of the premovement period (-1400 to -120 ms relative to keypress) corresponding to the features shown in Fig. 1, the error increased with faster tap rates, see Table I. Nevertheless the highest information transfer rate was obtained at the highest speed (0.5s) for the RP feature and at medium speed (1s) for the ERD feature. This finding, indicating that the refractory period is shorter for RP, needs to be studied in more subjects. This preliminary study indicates that different types of features are available for the prospective identification of movement intentions and that higher bit rates can be achieved in tapping speeds of 60 kpm and faster. Further investigation with more subjects will include ERD/ERS effects in the β frequency range, systematic comparison of the discriminability of different features and classification analysis using combined RP+ERD features, cf. [15].

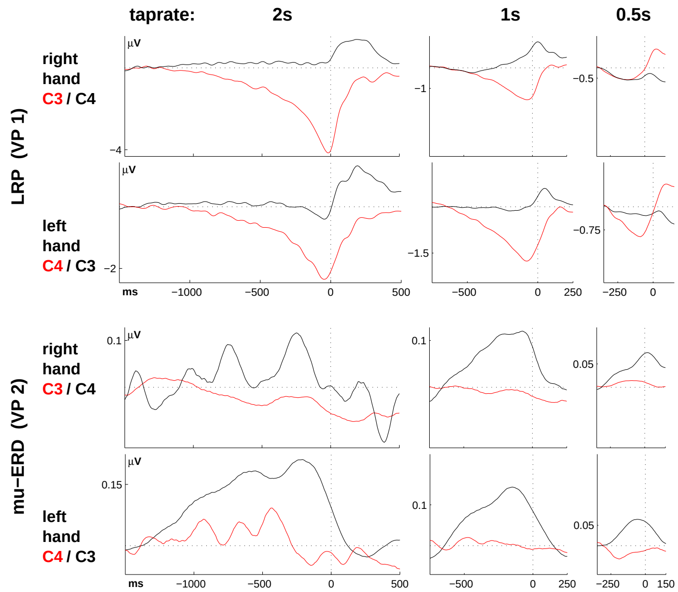

Fig. 1. Averaged data for RP (readiness potential) in VP 1 and ERD (event related desynchronization) of the μ rhythm (8–14 Hz) in VP 2. The tap-rate varies from 2s in the leftmost to 0.5s in the rightmost column. The black line in all subplots shows the activation over ipsilateral cerebral cortex before/after finger movement. The red line shows the activation over contralateral cerebral cortex before/after finger movement.

TABLE I

ERROR RATES (FIRST ROW) AND ESTIMATED BIT-RATES (SECOND ROW) FOR THE CLASSIFICATION OF SINGLE PREMOVEMENT TRIALS USING RP FEATURES (VP 1) AND ERD/ERS FEATURES (VP 2).

		Tap-rate		
		2s	1s	0.5s
VP 1 (RP):	ERR [%]	5.3	18.0	19.1
	ITR [bpm]	18.6	20.0	52.9
VP 2 (ERD):	ERR [%]	15.7	17.7	26.9
	ITR [bpm]	11.9	19.7	16.9

B. Exploring the limits of single-trial classification with fine spatial resolution

The information transmission rate of BCIs can be improved if single-trial analyses of movement-related scalp EEG parameters could reflect not only the gross somatotopic arrangement of, e.g., hand vs. foot, but also the finely graded representation of individual fingers, potentially enabling a kind of 'mental typewriting'.

To examine the quality of single-trial classification of BCI signals from close-by brain regions we recorded 128-channel EEGs of 14 healthy volunteers during selfpaced keypressing with finger II or V of either hand.

The data were analyzed as follows: First, we used standard averaging (time window -150 to -50 ms prior to keypress) for statistical analysis, i.e., class-wise difference (e.g., 'left V' minus 'left II') of these averaged potentials divided by

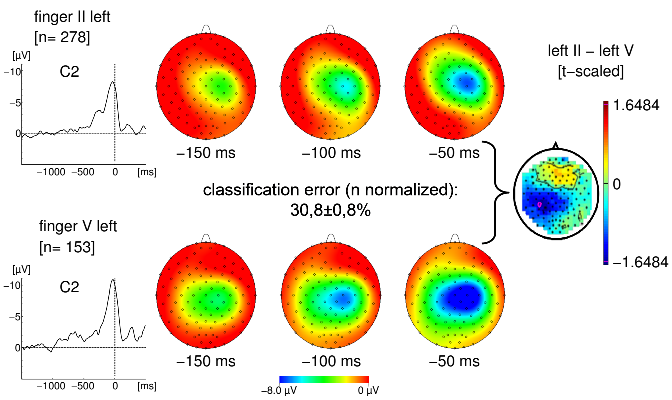

Fig. 2. Typical subject with clear and significantly distinguishable RP topographies associated with movements of finger II vs. finger V. Surprisingly the strongest difference is found at ipsilateral side ($p < 0.05$, see magenta coloured field in the left hemisphere of the scalp on the right).

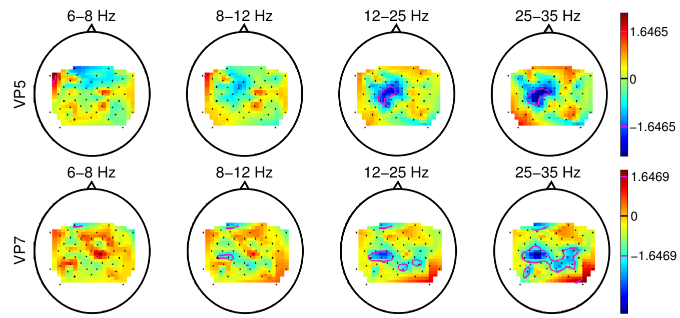

Fig. 3. Scalp topographies of ERD/ERS. t-scaled power-differences between phantom-movement and rest. The areas, where a significance level of $p = 0.05$ is reached, are circumscribed by a magenta-colored line. Upper row: an example for contralateral ERD of μ- and β-activity (VP5 with right hand amputation). Lower row: an example for a bilateral, mainly ipsilateral ERD of μ- and β-activity (VP7 with left hand amputation).

the estimated joint variance obeying a Student's t-distribution. These values indicate the significance of the class differences at level $p < 0.05$ when the respective threshold is exceeded in one direction. Second, we used the BBCI linear classifier for single-trial analyses [6].

The results can be grouped in three categories: (a) In 19% of the datasets we identified distinguishable topographies of the premovement negativity and obtained classification results well above chance level (error rates range between 19–37%, see Fig. 2).

(b) The second category (50.0% of the datasets) showed distinguishable topographies but classification results near chance level (error rates range between 45% and 47%). (c) Finally we found a third category (31% of the datasets) with weak negativation of one of the two classes, resulting in high differences between the mean amplitudes of the two classes and therefore in classification results well above chance level (error rates range between 23% and 38%).

The fact that it is in principle possible to distinguish the non-invasively recorded RPs associated with movements of fingers within the same hand in single trial analysis encourages us in our efforts to improve the technical facilities necessary to gather these existing physiological informations properly and non-invasively.

C. Detection of 'phantom limb commands'

Amputees might use BCIs to trigger movements of an electromechanical prosthesis. Accordingly, we elaborated on the standard BBCI paradigm to extend the usual 128-channel EEG recordings also to patients with traumatic amputations of one arm or hand. Specifically, we searched readiness potentials (RP) and event-related desynchronization (ERD) associated with real finger movements (intact side) and phantom (disabled side) finger movements.

We solved the problem of acquiring premovement brain activity of phantom movements which lack a time marker signal such as a keypress in the following way: The patients listened to an electronic metronome with two tones of alternating pitch. While the deep sound indicated rest, concomitant with the higher sound they had to perform either a finger tap on a keyboard using the healthy hand or a phantom movement with a phantom finger. Accordingly the absence of a keypress allows the post-hoc identification of an phantom finger movement intention and its approximate timing without cued reaction paradigm.

We studied eight patients (1 w, 7 m; age 37–74 years) with amputations between 16 and 54 years ago. Here, we report first results concerning the ERD. Remarkably, we found that all 8 patients showed significant ($p < 0.05$) 'phantom-related' ERD of μ- and β-frequencies (interval: -600 to 0 ms relative to the beat) at the primary motor cortex: 4 patients over the contralateral hemisphere, and 4 patients bilaterally, with 3 of them showing the larger ERD ipsilaterally (Fig. 3). These preliminary results encouraged the ongoing further analyses on RP of phantom movements and on error rates of off-line single-trial classifications which eventually could form a basis for BCI-control of a prosthesis driven by phantom limb motor commands.

III. Approach 2: BCI Control based on Imagined Movements without Subject Training

The RP feature presented in the previous section allows an early distinction between motor related mental activities since it reflects movement intent. But even in repetative movements the discrimination decays already after about 1 second, cf. [16]. Accordingly we take an alternative approach for the design of proportional BCI-control, like continuous cursor control. Here we focus on modulations of sensorimotor rhythms evoked by imagined movements. Our first feedback study ([17]) demonstrates that it is possible to do so following our philosophy of minimal subject training while still obtaining high information transfer rates.

A. Experimental Setup

We designed a fixed setup for a feedback study with 6 subjects who all had no or very little experience with BCI feedback. Brain signals were measured from 118 electrodes mounted on the scalp. To exclude the possibility of influence from non central nervous system activity, EOG and EMG were recorded additionally. Those channels were not used to generate the feedback signal.

Each experiment began with a so called calibration measurement in which labeled trials of EEG data during motor imagery were gathered. This data is used by signal processing and machine learning techniques to estimate parameters of a brain-signal to control-signal translation algorithm, cf. [17]. This algorithm can be applied online to continuously incoming signals to produce an instantaneous feedback.

In the calibration measurement 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 was interrupted by periods of random length, 1.75 to 2.25s, in which the subject could relax.

Then the experimenter investigated the data to adjust subject-specific parameters of the data processing methods and identified the two classes that gave best discrimination. When this discrimination was satisfactory, a binary classifier was trained and three different kinds of feedback application followed. All data of each subject were recorded on the same day (calibration plus three feedback applications).

During preliminary feedback experiments we realized that the initial classifier often was performing suboptimal, such that the bias and scaling had to be adjusted. Later investigations have shown that this adaption is needed to account for the different experimental condition of the (exciting) feedback situation as compared to the calibration measurement.

In the first feedback application (‘position controlled cursor’), the output of the classifier was directly translated to the horizontal position of a cursor. There were two target fields on the left resp. right edge of the screen, one of which was highlighted at the beginning of a trial. The cursor started in a deactivated mode (in which it could move but not trigger a target field) and became activated after the user has held the cursor in a central position for 500 ms. The trial ended when the activated cursor touched one of the two target fields. That field was then colored green or red, depending on whether it was the correct target or not. The cursor was deactivated and the next target was highlighted.

The second feedback application (‘rate controlled cursor’) was very similar, but the control of the cursor was relative to the actual position, i.e., at each update step a fraction of the classifier output was added to the actual cursor position. Each trial started by setting the cursor to the middle of the screen and releasing it after 750 ms.

The last feedback application (‘basket game’, similar to applications in [18] and [19]) operated in a synchronous mode. A ball was falling down at constant speed while its horizontal position was controlled by the classifier output. At the bottom of the screen there were three target fields, the outer having half the width of the middle fields to account for the fact that outer positions were easier to hit.

B. Results

To compare the results of the different feedback sessions we use the information transfer rate (ITR, [1]) measured in bits per minute (bpm). In contrast to error rates or ROC curves the ITR takes different duration of trials and different number of classes into account. Table II summarizes the information transfer rates that were obtained by the 6 subjects in the three feedback sessions. Highest ITRs were obtained in the ‘rate controlled cursor’ scenario which has a asynchronous protocol.

TABLE II

THE FIRST TWO COLUMNS COMPARE THE ACCURACY AS CALCULATED BY CROSS-VALIDATION ON THE CALIBRATION DATA WITH THE ACCURACY OBTAINED ONLINE IN THE FEEDBACK APPLICATION ‘RATE CONTROLLED CURSOR’. COLUMNS THREE TO EIGHT REPORT THE INFORMATION TRANSFER RATES (ITR) MEASURED IN BITS PER MINUTE. OBTAINED IN ALL FEEDBACK APPLICATIONS FOR EACH FEEDBACK APPLICATION THE FIRST COLUMN REPORTS THE AVERAGE ITR OF ALL RUNS (OF 25 TRIALS EACH), WHILE THE SECOND COLUMN REPORTS THE PEAK ITR OF ALL RUNS. SUBJECT 2 DID NOT ACHIEVE BCI CONTROL (64.6% ACCURACY IN THE CALIBRATION DATA).

	acc [%]		cursor pos.c.		cursor rate c.		basket	
	cal.	fb.	overall	peak	overall	peak	overall	peak
1	95.4	80.5	7.1	15.1	5.9	11.0	2.6	5.5
3	98.0	98.0	12.7	20.3	24.4	35.4	9.6	16.1
4	78.2	88.5	8.9	15.5	17.4	37.1	6.6	9.7
5	78.1	90.5	7.9	13.1	9.0	24.5	6.0	8.8
6	97.6	95.0	13.4	21.1	22.6	31.5	16.4	35.0
∅	89.5	90.5	10.0	17.0	15.9	27.9	8.2	15.0

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

In a later experiment subject 3 operated a mental typewriter based the second feedback application. The alphabet (including a space and a deletion symbol) was split into two parts and those groups of characters were placed on the left resp. right side of the screen. The user selects one subgroup by moving the cursor to the respective side and the process is iterated until a ‘group’ of one character is selected. The splitting was done alphabetically based on the probabilities of the German alphabet, but no elaborated language model was used. In a free spelling mode subject 3 spelled 3 german sentences with a total of 135 characters in 30 minutes, which is a typing speed of 4.5 letters per minutes. Note that all erros have been corrected by using the deletion symbol. For details, see [16].

C. Investigating the Dependency of BCI Control

The fact that it is in principle possible to voluntarily modulate motorsensory rhythms without concurrent EMG activity was studied in [20]. Nevertheless it has to be checked for every

BCI experiment involving healthy subjects. For this reason we always record EMG signals even though they are not used in the online system. On one hand we investigated classwise averaged spectra, their statistical significant differences and the scalp distributions and time courses of the power of the μ and β rhythm. The results substantiated that differences of the motor imagery classes indeed were located in sensorimotor cortices and had the typical time courses (except for subject 2 in whom no consistent differences were found). On the other hand we compared how much variance of the classifier output and how much variance of the EMG signals can be explained by the target class. Much in the spirit of [20] we made the following analysis using the squared bi-serial correlation coefficient r^2. The r^2-value was calculated for the classifier output and for the band-pass filtered and rectified EMG signals of the feedback sessions. Then the maximum of those time series was determined resulting in one r^2-value per subject and feedback session for EMG resp. for the BCI classifier signal. The r^2 for EMG was in the range 0.01 to 0.08 (mean 0.04±0.03) which is very low compared to the r^2 for the BCI classifier signal which was in the range 0.36 to 0.79 (mean 0.52±0.15). The fact that the BBCI works without being dependent on eye movements or visual input was additionally verified by letting two subjects control the BBCI with closed eyes which resulted in a comparable performance as in the closed loop feedback.

IV. Lines of Further Improvement

A. Combination of Different Features

Significant gain can be expected from a combination of several single features if these single features provide complementary information for the classification task. In case of sensorimotor cortical processes accompanying finger movements Babiloni et al. [21] demonstrated that RP and ERD indeed show up with different spatio-temporal activation patterns across primary (sensori-)motor cortex (M-1), supplementary motor area and the posterior parietal cortex. This finding is backed by invasive (subdural) EEG recordings [22] during brisk, self-paced finger and foot movements.

These observations led us to the theoretical investigation of how to combine several single features. (Note that single feature does not mean one dimensional feature.) Technically speaking, given several feature vectors, the question is how to optimally combine the information, i.e., when classifying the joint features we expect a better result than with the best single feature. Techniques suggested in the literature are voting, using a meta classifier or a winner-takes-all strategy. When applied to our BCI problem with RP and ERD derived features all these method did not (or only marginally) improve the classification accuracy compared to the classification of the best single feature in our setting. A substantial gain in classification could be obtained only after incorporating a-priori knowledge into the feature combination. We made the assumption that the feature vectors reflecting ERD and RP effects indeed are independent. Under a gaussian assumption we were able to derive the optimal method of combining features, that turns out to be simple, cf. [23], [15]. It can be described as quaderatic discriminant analysis (QDA), where cross-feature coefficients in the estimated covariance matrix are set to zero. Additionally assuming equal covariance matrices leads to a linear feature combination variant. Even when these assumptions are not met perfectly in practice, a good performance by the novel method can be expected.

B. CSSP: CSP with simultaneous spectra optimization

The idea of the CSSP algorithm ([24]) is to optimize very simple frequency filters (with one delay tap) for each channel at the same time as the spatial filters in the CSP algorithm.

Given s_i, the signal s_i^τ is defined to be the signal s_i delayed by τ ms. In CSSP the usual CSP approach is applied to the concatenation of s_i and s_i^τ in the channel dimension, i.e., the delayed signals are treated as new channels. By this delay embedding the CSP analysis is solved in the state space, allowing to neglect or emphasize specific frequency bands at each electrode position. The performance of the method depends on the choice of τ which can be accomplished by some validation approach on the calibration data. More complex frequency filters can be found by concatenating more EEG-signals with several delays. But in [24] it was concluded that in typical BCI situations where only small training sets are available, the choice of only one delay step is most effective. Different approaches that implement one global but more complex spectral filter into CSP are under investigation.

V. Discussion and Outlook

The Berlin Brain-Computer Interface project makes use of a machine learning approach towards BCI. Working with high dimensional, complex features obtained from 128 channel EEG allows the system a distinct flexibility for adapting to the specific individual characteristics of each user's brain.

In one line of investigation we studied the detectability of premovement potentials in healthy subjects. It was shown that high bit rates in single-trial classifications can be achieved by fast-paced motor commands. An analysis of motor potentials during movements with finger II and V within one hand exposed a possible way of further enhancement. A preliminary study involving patients with traumatic amputations showed that the results can in principle be expected to transfer to phantom movements. A restriction seems to be that the detection accuracy decreases with longer loss of the limb.

In a second approach we investigate the possibility of establishing BCI control based on motor imagery without subject training. 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, and (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 II.

Recent BBCI activities comprise (a) mental typewriter experiments, with an integrated detector for the error potential, an idea that has be investigated off-line in several studies, cf. [6], [25], [26], [27], (b) the online use of combined feature and multi-class paradigms and (c) real-time analysis of mental workload in subjects engaged in real world cognitive tasks, 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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