Boosting bit rates and error detection for the classification of fast-paced motor commands based on single-trial EEG analysis

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Abstract—**Brain-Computer-Interfaces (BCI) involve two coupled adapting systems: the human subject and the computer. In developing our BCI, our goal was to minimize the need for subject training and to impose the major learning load on the computer. To this end, we use behavioral paradigms that exploit single-trial EEG potentials preceding voluntary finger movements. Here, we report recent results on the basic physiology of such pre-movement event-related potentials (ERP): 1) We predict the laterality of imminent left vs. right hand finger movements in a natural keyboard typing condition and demonstrate that a single-trial classification based on the lateralized Bereitschaftspotential (BP) achieves good accuracies even at a pace as fast as 2 taps per second. Results for 4 out of 8 subjects reached a peak information transfer rate of more than 15 bits per minute (bpm); the 4 other subjects reached 6-10 bpm. 2) We detect cerebral error potentials from single false-response trials in a forced-choice task, reflecting the subject's recognition of an erroneous response. Based on a specifically tailored classification procedure that limits the rate of false positives at, e.g. 2 %, the algorithm manages to detect 85 % of error trials in 7/8 subjects. Thus, concatenating a primary single-trial BP-paradigm involving finger classification feedback with such secondary error detection could serve as an efficient on-line confirmation/correction tool for improvement of bit rates in a future BCI setting. As the present variant of the Berlin BCI (BBCI) is designed to achieve fast classifications in normally behaving subjects, it opens a new perspective for assistance of action control in time-critical behavioral contexts; the potential transfer to paralysed patients will require further study.**

Keywords—**brain-computer interface, Bereitschaftspotential, error potential, single-trial analysis, multi-channel EEG, linear classification, Fisher's discriminant**

I. Introduction

The aim of brain-computer interface (BCI) research is to build a communication system that is capable of translating a subject's intention—reflected by suitable brain signals—into a control signal. The required discrimination of different brain states may be based on *evoked potentials* (like steady-state visual evoked potentials or P300) or on *endogenous brain signals* (like movement-related potentials). Exploited features are, e.g., slow potential variations, rhythmic features, or indices of signal dynamics (see this special issue). In a first step, a one-dimensional quantity (control signal) is commonly computed from spontaneous EEG and then used for feedback purposes. Systems based on slow cortical potentials use mainly self-regulation of cortical negativity vs. positivity for cursor control *without an explicit setting that binds the cursor movement to a motor intention.* Other systems explicitly involving motor intentions use oscillatory features like event-related desynchronisation (ERD) of the μ- and/or central β-rhythm.

In this contribution, we describe three aspects of our Berlin BCI (BBCI) development program: (a) We exploit advanced machine learning and signal processing technology for single-trial EEG evaluation requiring *no* prior subject training. (b) We use *slow pre-movement potentials* as physiological signals, and (c) we utilize a fast-paced experimental paradigm.

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II. Our approach

Concept. The leitmotiv of the BBCI development program is 'let the machines learn', i.e., we want to minimize the need for the subject to learn predefined brain commands for future BCI feedback. To this end, the machine should learn to recognize the neuronal signatures of the subject's natural cerebral motor commands. Accordingly, we chose a paradigm in which well-established competences, automatic in daily life, are coupled to naturally related control effects. The basic working example for this natural coupling is that the command preparation of a left (or right) hand movement moves the cursor the in left (or right) direction.

Paradigm. We let our subjects (all without neurological deficit) make a binary (left/right hand) decision coupled to a motor output, i.e., self-paced typewriting on a computer keyboard. Using multi-channel scalp EEG recordings, we analyze the single-trial differential potential distributions of the Bereitschaftspotential (BP) preceding voluntary (left or right hand) finger movements over the corresponding (right/left) primary motor cortex. As we study brain signals from healthy subjects executing real movements, our paradigm requires a capability to predict the laterality of imminent hand movements prior to any EMG activity in order to exclude a possible confound with afferent feedback from muscle and joint receptors contingent upon an executed movement.

Features of brain signals. We currently investigate non-oscillatory event-related potentials (ERPs). Our choice of ERPs is based on two concerns, one neurophysiological and one data analytical:

(a) Most endogenous rhythmic brain activities reflect *idling rhythms*. If a BCI command is defined as attenuation of an idling rhythm, it implies that a prerequisite for evoking such a BCI command is the stable presence of that rhythm. This could become a problem when operating the BCI at a fast pace as at least some pericentral idling rhythms will not be fully recovered [1]. In contrast, we propose that slow pre-movement ERP features can follow a fast command-pace.

(b) From the perspective of data analysis, the important question is how to classify the noisy and high-dimensional EEG data. As will be argued below, the distribution of ERP features for one condition is normal with the mean determined by task-related brain activity and with the covariance matrix determined by non-task-related components. This makes the problem of discriminating trials from different tasks linear. Linear models thus provide better classification generalization than do more complex non-linear models when the number of training samples is limited as is typical in the case of BCI paradigms.

Preprocessing. To extract relevant spatio-temporal features of slow brain potentials, we subsample signals from all or a subset of all available channels and take them as high-dimensional feature vectors. Here subsampling is accomplished simply by calculating means of consecutive, non-overlapping intervals, i.e., given a trial $\langle x_c(n) \mid n = 0, \ldots, N-1 \rangle$ in one channel c we calculate

$$\hat{x}_c(n) = {}^1\!/_T \sum_{t<T} x_c(nT+t) \quad n = 0, \ldots, {}^N\!/_T - 1.$$

which is x_c subsampled by an integer factor T. The concatenation of those $\hat{x}_c$'s of all channels gives the full feature vector henceforth called 'ERP features'. It can be regarded either as a time series in multiple channels or as a sequence of several scalp maps. This simple preprocessing method gave very good results in our experiments when used in conjunction with a well regularized classifier, see below. We apply special treatment to trials in which most information is expected to appear at the end of the given interval, as it is naturally the case with pre-movement trials. Starting points are epochs of 128 samples of raw EEG data as depicted in Fig. 1 (a) for one channel. To emphasize the late signal content, we first multiply the signal by a one-sided cosine function, (Fig. 1 (b)),

$$w(n) := 1 - \cos({}^{n\pi}\!/_{128}) \quad \text{for } n = 0, \ldots, 127,$$

before applying a Fourier transform (FT) filtering technique: >from the complex-valued FT coefficients all are discarded but the ones in the pass-band (including the negative frequencies, which are not shown), (Fig. 1 (c)). Transforming the selected bins back into the time domain gives the smoothed signal of which the last 200 ms are subsampled at 20 Hz (explained above) resulting in 4 feature components per channel (Fig 1(d)).

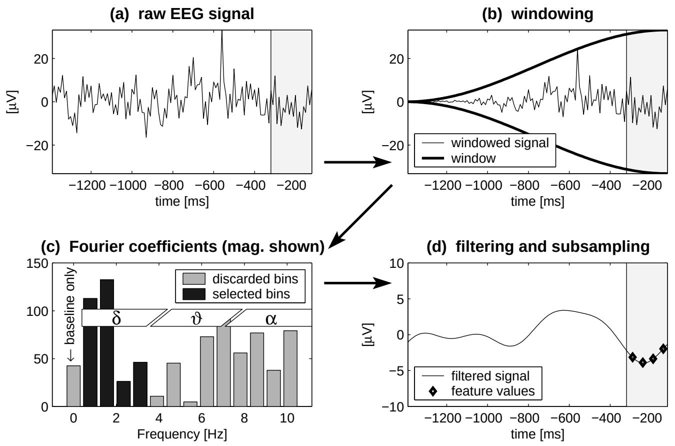

Fig. 1. This example shows the feature calculation in one channel of a pre-movement trial [-1400 -120] ms with keypress at $t = 0$ ms. The pass-band for the FT filtering is 0.4–3.5 Hz and the subsampling rate is 20 Hz. Features are extracted only from the last 200 ms (shaded) where most information on the upcoming movement is expected.

For the results presented here, we used the same settings (interval length, pass-band, channels) for all subjects.

Distribution of ERP features. The ERP features are superpositions of task-related and many task-unrelated signal components. The mean of the distribution across trials is the non-oscillatory task-related component (ERP), ideally the same for all trials. The covariance matrix depends only on task-unrelated components. Our analysis showed that the distribution of ERP features is indeed normal, (Fig. 2). The covariance matrices are calculated only from one 'time slice' of the ERP features, i.e., for a fixed time prior to a key stroke $t = -110$ ms. Along each axis of the matrices, EEG channels are sampled in lines from frontal to occipital scalp, each line going from left to right hemisphere, thereby causing the lattice structure of the covariance matrices. The important observation here is that the covariance matrices of both classes look very much alike.

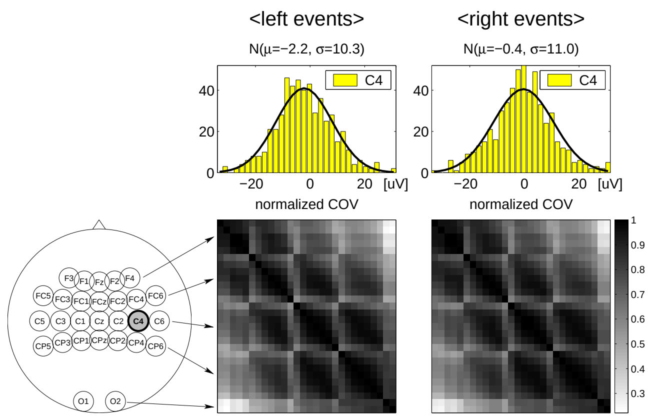

Fig. 2. Histograms show the distribution of ERP features at channel C4 at a fixed time point overlaid by a fitted normal distribution. The normalized covariance matrices across channels for the two conditions (left vs. right hand finger movement preparation) have only minor differences most probably induced by noise.

The minor differences probably reflect noise and are ignored by linear classification whereas they are a potential concern for non-linear classifiers.

Classification. A basic result from the theory of pattern-matching [2], says that Fisher's Discriminant gives the classifier with minimum probability of misclassifications for known normal distributions with equal covariance matrices. As was pointed out in the previous paragraph, the classes of ERP features can be assumed to obey such distributions. But since the true distribution parameters are unknown, the means and covariance matrices have to be estimated from training data. With only a limited amount of training data at our disposal, this approach is prone to error. To overcome this problem, we regularize the estimation of the covariance matrix. In the mathematical programming approach of [3] the following quadratic optimization has to be solved in order to calculate the Regularized Fisher Discriminant (RFD) w from data x_k and labels $y_k \in \{-1, 1\}$ $(k = 1, \ldots, K)$:

$$\min_{w,b,\xi} \ {}^1\!/_2 \, \|w\|_2^2 \ + \ {}^C\!/_K \, \|\xi\|_2^2 \quad \text{subject to}$$

$$y_k(w^\top x_k + b) = 1 - \xi_k \quad \text{for } k = 1, \ldots, K$$

where $\|\cdot\|_2$ denotes the ℓ_2-norm ($\|w\|_2^2 = w^\top w$), ξ are slack variables and C is a model parameter which has to be estimated from training data. From this formulation other variants can be derived. For example, using the ℓ_1-norm in the regularizing term enforces sparse discrimination vectors.

Other regularized discriminative classifiers like support vector machines (SVMs) or linear programming machines (LPMs) appear to be equally suited for the task [4].

III. Summary of Two Studies on Classifying ERPs

A. Experimental Setup

We recorded brain activity from 8 subjects with multi-channel EEG amplifiers using 32, 64, or 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, as well as horizontal and vertical EOG signals, were recorded. An important characteristic of our present analysis was to refrain from any trial rejection because of eventual artifacts so as to enforce robust classifications.

B. Prediction of Laterality in Fast Self-Paced Motor Commands

Experiment. In this experiment, the subject was sitting in normal typing position at a computer keyboard pressing one of four keys, using the index or little finger of the right or left hand, in a self-chosen order and timing. An approximate tapping pace was announced by the operator before each six-minute recording session. Most subjects took part in experiments with 0.5, 1 and 2 taps per second (tps).

Objective. Our goal was to predict in single-trials the laterality of imminent left vs. right finger movements at a time-point prior to the onset of EMG activity. The specific ERP feature that we use is the lateralized Bereitschaftspotential (BP). Neurophysiologically, the BP is well investigated and described [5], [6]. New questions that arise in this context are (a) is the BP observable also in fast motor sequences, and (b) can the lateralization be discriminated on a single-trial basis.

Analysis. Our investigations provide positive answers to both questions. Fig. 3 shows the ERPs of left and right hand finger taps at a pace of 2 taps per second. The investigation of the Bereitschaftspotential in fast motor sequences performed by healthy subjects requires consideration of how aftereffects of one movement superimpose on the preparation of a consecutive movement. For the present paradigm, the subjects were instructed to balance the transition matrix for left/right hand movements sequences so that, e.g., a right hand movement was preceded by left/right hand movements in equal proportions. Furthermore, the classification does not involve the determination of a baseline.

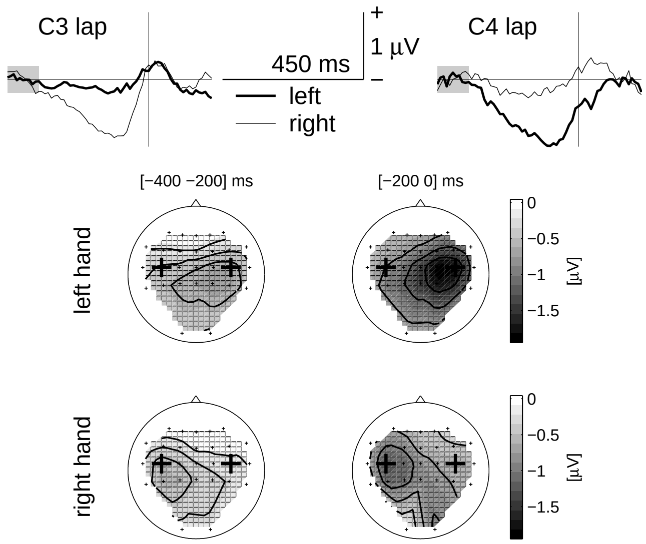

Fig. 3. Grand average at ERPs at Laplace filtered locations from a self-paced typing experiment with 2 taps per second with keypress at $t = 0$ ms. The lateralization of the Bereitschaftspotential is clearly specific for left resp. right finger movements. The gray bar -450 to -350 ms indicates the baseline interval. Potential maps show the scalp topographies of the BP (positions C3/C4 are marked by a cross).

It is important to keep in mind that our studies so far involve real movements performed by healthy subjects. This makes it important to verify that our EEG-based classification does not rely on information from afferent nerves. One way to determine this is to compare EEG- and EMG-based classification. Fig. 4 shows the time course of classification. Here classification at a given time point t means that each single trial ERP feature was calculated from windows with endpoint t. Thus, the results are causal, i.e., data of each single trial received after this time point (relative to keypress) do not enter preprocessing and classification.

As shown in Fig. 4, we chose $t = -120$ ms as the time-point for classification. For each of our experiments a suit-

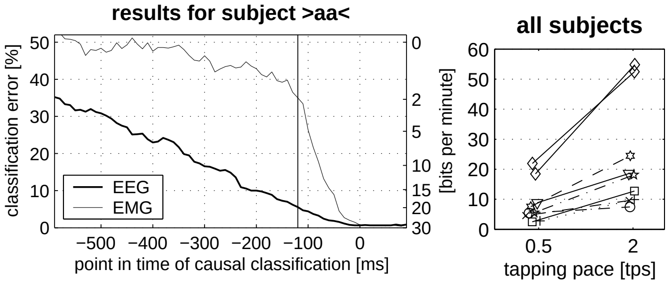

Fig. 4. *Left panel:* Comparison of EEG and EMG based classification with respect to the endpoint of the classification interval with $t = 0$ being the time point of keypress. The vertical line marks the time point chosen for evaluating the classification in terms of information transfer rates. These results come from an experiment with an approximate average pace of 0.5 taps per second. *Right panel:* Bit-rates for all subjects with tapping pace 0.5 and 2 tps. Results from the best subject *aa* were reproduced in a second experiment (marker ⋄).

able time point was found between 130 and 100 ms prior to keypress. Preprocessing was performed as described in Sec. II with pass-band 0.4–3.5 Hz and subsampling at 20 Hz in the same manner as is shown in Fig. 1. All channels in the rectangle FC5, FC6, CP6, CP5 plus P3, P4 were used.

Results. One performance measure that can compare the efficiency of BCI systems with respect to classification accuracy, command speed, and number of possible commands is the theoretical information transfer rate given by Shannon's theorem, as discussed in [7]. This rate in bits per minute is given by $^{60}/_{pace}B$, where *pace* is the average inter-command interval in seconds and $B = \log_2 N + p \log_2 p + (1-p)\log_2(^{1-p}/_{N-1})$ is the number of bits per selection from N choices with probability p for correct classification. Here we use bit rates to measure the discrimination performance of pre-movement trials.

For 7 out of 8 subjects, the fastest tap performance (2 tps) worked efficiently, with bit rates about twice as high as in the 0.5 tps experiment. For the 8th subject (marker ∘ in Fig. 4) there was no substantial improvement. The subject-specific peak bit rate, according to the above mentioned measure, was between 6 and 10 bits per minute (bpm) for 4 subjects and above 15 bpm for another 4 subjects.

C. Detection of Error Potentials

Objective. One additional ('second-pass') strategy to enhance classification accuracy for a future BCI setting, in particular for subjects who are facing a substantial fraction of 'first-pass' BCI classification errors, is a verification (of the first-pass classification) based on the detection of a cerebral *error potential*, as proposed in [8]. To assess how our pattern-matching approach works on this problem we analyzed data from a variant of the 'd2-test' of attention [9].

Experiment. Subjects were asked to respond to targets displayed on a computer screen (the symbol *d* with bars in two of four possible positions) by pressing a key with the right index finger and to non-targets with the left index finger. After the subject's keystroke, the reaction time was displayed on the screen, either in green if the response was correct (target hit or correct rejection), or in red if it was erroneous (target miss or false alarm). The next trial began 1.5±0.25 s later. A more detailed description and analysis of this experiment can be found in [10].

Analysis. The average *miss-minus-hit* difference potential in Fig. 5 shows two characteristic components: a negative wave called error negativity (N_E) with fronto-central maximum and a susequent broader positive peak labeled as error positivity (P_E) with centro-parietal maximum, [11]. According to recent studies, P_E is connected to conscious error detection [12], and thereby specific to errors, whereas N_E seems to reflect mainly a comparison process. N_E occurs also in correct trials but later and with smaller amplitude [13].

Preprocessing was performed as described in Sec. II (without FT filtering) with subsampling at 20 Hz in the time interval 0–300 ms relative to the motor response. All channels in the vicinity of the vertex were used, i.e., the ones within the rectangle F3, F4, P4, P3.

For the classification of the error potential in single trials, we can, in principle, use the same approach as above. However, we introduced one small but psychologically crucial modification: our response verification algorithm set strict boundaries on the rate of detection of false positives (FP-rate) of first-pass errors. We did so because repeated false second-pass rejections of BCI trials, which had been correctly classified in the first-pass, would be detrimental.

We have previously shown [10] that, under the assumption that the classes of correct and erroneous ERP features have known normal distributions with equal covariance matrices, the Bayes optimal classifier realizing a predefined FP-bound uses Fisher's Discriminant with adapted bias.

Results. Based on this apporach more than 85 % of errors at a predefined rate of false positives as low as 2 % could be detected within 300 ms after the response in 7 out of 8

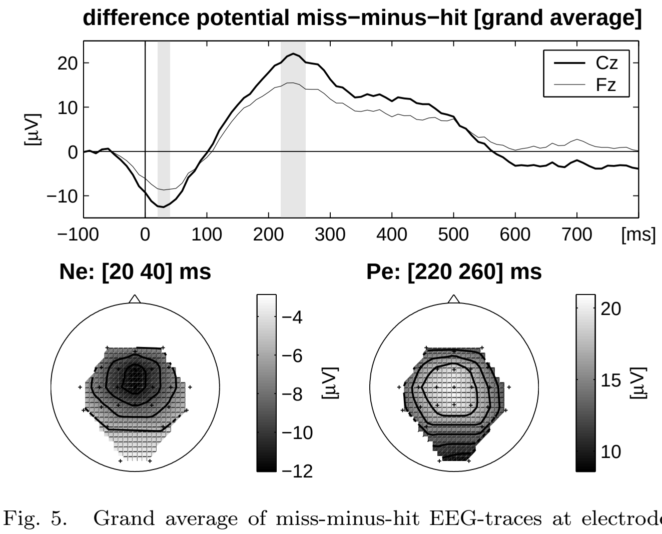

Fig. 5. Grand average of miss-minus-hit EEG-traces at electrodes Cz, Fz where $t = 0$ ms is at keystroke response. Time windows of N_E and P_E are shaded and corresponding scalp maps are shown below.

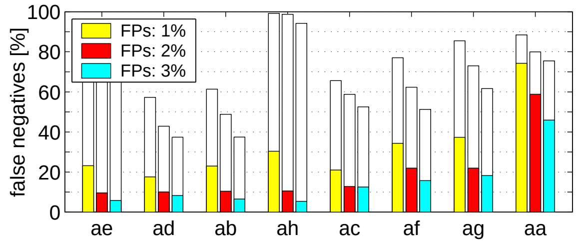

Fig. 6. Rate of false negatives (FN) for error detection at 300 ms with false positive rate fixed at 1, 2, or 3 % for 8 subjects *aa*–*ah*. White bars show the corresponding FN-rates for the amplitude criterion, as suggested earlier in [8].

subjects. Fig. 6 shows the results for all subjects at FP-rates of 1, 2 and 3 %. The application of the amplitude threshold criterion, as proposed in [8] under the constraint of a given FP-rate led considerably higher rates of false negative classifications as indicated by white bars in Fig. 6.

Accordingly, this approach can be expected to provide a valuable add-on tool for improving BCI bit rates by an online EEG-based detection of first-pass classification errors.

IV. Discussion

A characteristic feature of the present paradigm is the exploitation of slow pre-movement Bereitschaftpotentials (BPs). We could confirm our hypothesis that these BPs could be used efficiently for single-trial classifications also at motor command rates as fast as two finger tappings per second, i.e., at a motor command rate of 120 binary decisions (left/right hand) per minute. This value defines a substantial margin for possible algorithmic improvements, e.g., by introducing artifact handling which can be integrated easily in the present procedures. Here, it appears of interest that the one subject with prior experience in EEG-recordings and a low incidence of artifacts, achieved the highest bit rate ($>$ 50 bits per minute).

The data as reported here were from time windows defined by the keystrokes, i.e., they were identified post-hoc and not prospectively from the arriving data stream. Presently ongoing studies on analyses of continuously arriving data streams show that BPs can be identified even without any trigger being available, albeit at a lower hit rate, cf. [4]. Interestingly, the discrimination performance could be boosted potentially by adding to a first-pass single-trial classification of motor commands a second-pass detection of error potentials generated by the subjects observing a feedback of the first-pass classification.

We like to emphasize that the paradigm is shaped presently for fast classifications in normally behaving subjects and thus could open interesting perspectives for a BCI assistance of action control in time-critical behavioral contexts. Notably, also a possible transfer to BCI control by paralyzed patients appears worthwhile to be studied further because these patients were shown to retain the capability to generate BPs with partially modified scalp topographies, [14].

Our paradigm is one variant of several non-invasive approaches to BCI, which all are designed to respect the integrity of an intact brain. These scalp-EEG approaches presumably will predominate in BCI-applications for healthy subjects. Their future for applications in patients will be influenced by the outcome of studies evaluating the short- and long-term consequences of invasive approaches in animal models. For the time being, the ease of surface EEG applications in human subjects, along with the minimal learning effort on part of the subjects, justify explorative studies in paralysed patients.

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