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 (BCIs) 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 premovement event-related potentials (ERP). 1) We predict the laterality of imminent left- versus 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/s. Results for four out of eight subjects reached a peak information transfer rate of more than 15 b/min; the four other subjects reached 6–10 b/min. 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 seven out of eight subjects. Thus, concatenating a primary single-trial BP-paradigm involving finger classification feedback with such secondary error detection could serve as an efficient online confirmation/correction tool for improvement of bit rates in a future BCI setting. As the present variant of the Berlin BCI 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 paralyzed patients will require further study.**

***Index Terms*—Bereitschaftspotential (BP), brain–computer interface (BCI), error potential, Fisher's discriminant, linear classification, multichannel EEG, single-trial analysis.**

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 versus 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 desynchronization (ERD) of the μ- and/or central β-rhythm.

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In this contribution, we describe the following three aspects of our Berlin BCI (BBCI) development program: 1) we exploit advanced machine learning and signal processing technology for single-trial EEG evaluation requiring *no* prior subject training; 2) we use *slow premovement potentials* as physiological signals; and c) we utilize a fast-paced experimental paradigm.

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 in the 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 multichannel 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 electromyogram (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 nonoscillatory event-related potentials (ERPs). Our choice of ERPs is based on two concerns—one neurophysiological and one data analytical.

1) 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 premovement ERP features can follow a fast command-pace.
2) 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 nontask-related components. This makes the problem of discriminating trials from different tasks linear. Linear models thus provide better classification generalization than do more complex nonlinear 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, nonoverlapping intervals, i.e., given a trial $\langle x_c(n) \,|\, n = 0, \ldots, N-1 \rangle$ in one channel c, we calculate

$$\hat{x}_c(n) = \frac{1}{T} \sum_{t<T} x_c(nT + t), \qquad n = 0, \ldots, \frac{N}{T} - 1$$

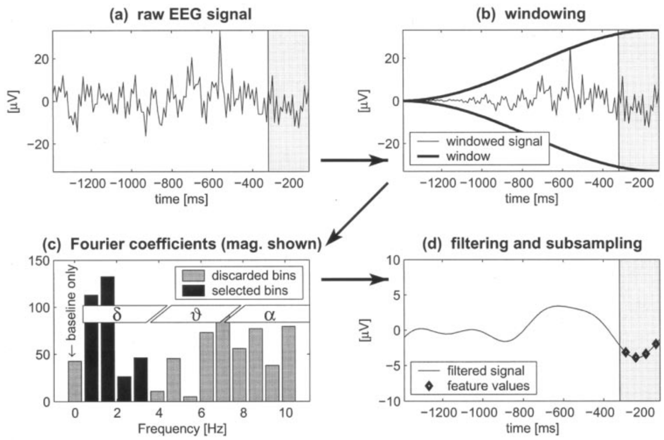

Fig. 1. This example shows the feature calculation in one channel of a premovement trial [-1400 -120 ms] with keypress at $t = 0$ ms. The passband for the FT filtering is 0.4–3.5 Hz and the subsampling rate is 20 Hz. Features are extracted only from the last 200 ms (shaded) where most information on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

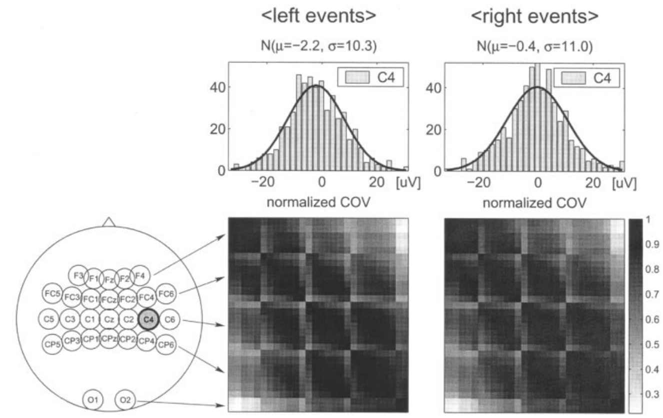

Fig. 2. Histograms show the distribution of ERP features at channel C4 at a fixed time point overlaid by a fitted normal distribution. The normalized covariance matrices across channels for the two conditions (left- versus right-hand finger movement preparation) have only minor differences most probably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

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 the following. 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 premovement 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)]

$$w(n) := 1 - \cos\left(\frac{n\pi}{128}\right), \qquad \text{for } n = 0, \ldots, 127$$

before applying a Fourier transform (FT) filtering technique: from the complex-valued FT coefficients all are discarded but the ones in the passband (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 previously) resulting in four feature components per channel [Fig. 1(d)].

For the results presented here, we used the same settings (interval length, passband, 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 nonoscillatory 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. The minor differences probably reflect noise and are ignored by linear classification, whereas they are a potential concern for nonlinear 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. However, 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 $y_k \in \{-1, 1\}$ $(k = 1, \ldots, K)$:

$$\min_{w,\, b,\, \xi} \frac{1}{2}\|w\|_2^2 + \frac{C}{K}\|\xi\|_2^2 \quad \text{subject to}$$
$$y_k\left(w^\top x_k + b\right) = 1 - \xi_k, \quad \text{for } k = 1, \ldots, K$$

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 eight subjects with multichannel EEG amplifiers using 32, 64, or 128 channels bandpass 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

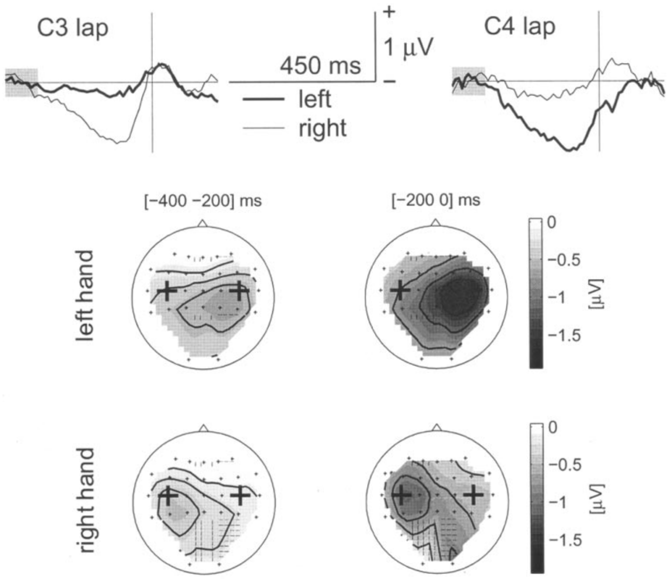

Fig. 3. Grand average at ERPs at Laplace filtered locations from a self-paced typing experiment with 2 taps/s with keypress at $t = 0$ ms. The lateralization of the BP is clearly specific for left and right finger movements. The gray bar -450 to -350 ms indicates the baseline interval. Potential maps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

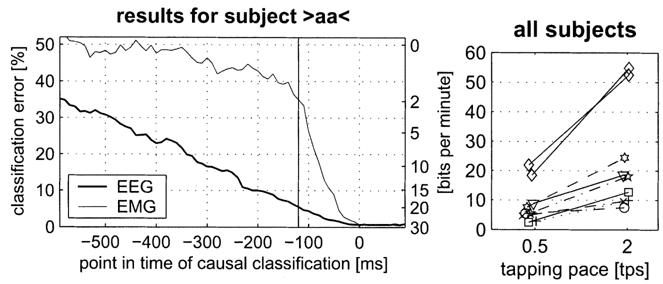

Fig. 4. (left) Comparison of EEG- and EMG-based classification with respect to the endpoint of the classification interval with $t = 0$ being the time point of keypress. The vertical line marks the time point chosen for evaluating the classification in terms of information transfer rates. These results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

and timing. An approximate tapping pace was announced by the operator before each 6-min recording session. Most subjects took part in experiments with 0.5, 1, and 2 taps/s.

Objective: Our goal was to predict in single-trials the laterality of imminent left- versus right-finger movements at a time-point prior to the onset of EMG activity. The specific ERP feature that we use is the lateralized BP. Neurophysiologically, the BP is well investigated and described [5], [6]. New questions that arise in this context are 1) is the BP observable also in fast motor sequences, and 2) 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/s. The investigation of the BP 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.

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 suitable time point was found between 130 and 100 ms prior to keypress. Preprocessing was performed as described in Section II with passband 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, and 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 $(60/\mathrm{pace})B$, where pace is the average intercommand 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 premovement trials.

For seven out of eight subjects, the fastest tap performance (2 taps/s) worked efficiently, with bit rates about twice as high as in the 0.5 taps/s experiment. For the eighth subject (marker $\circ$ in Fig. 4), there was no substantial improvement. The subject-specific peak bit rate, according to the previously mentioned measure, was between 6 and 10 b/min for four subjects and above 15 b/min for another four 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 nontargets 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 subsequent 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 Section II (without FT filtering) with subsampling at 20 Hz in the time interval 0–300 ms rel-

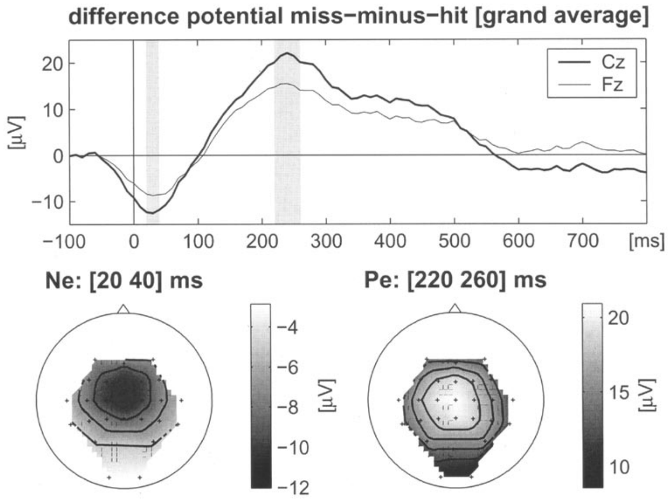

Fig. 5. Grand average of miss-minus-hit EEG-traces at electrodes Cz, Fz where $t = 0$ ms is at keystroke response. Time windows of N_E and P_E are shaded and corresponding scalp maps are shown.

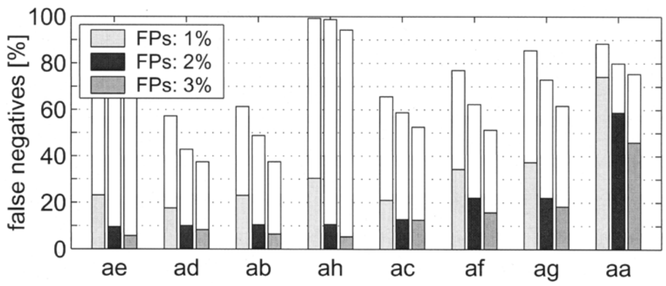

Fig. 6. Rate of false negatives (FN) for error detection at 300 ms with false positive rate fixed at 1, 2, or 3% for eight subjects *aa–ah*. White bars show the corresponding FN-rates for the amplitude criterion, as suggested earlier in [8].

ative to the motor response. All channels in the vicinity of the vertex were used, i.e., the ones within the rectangle F3, F4, P4, and P3.

For the classification of the error potential in single trials, we can, in principle, use the same approach as before. 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 approach, 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 seven out of eight 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. Conclusion

A characteristic feature of the present paradigm is the exploitation of slow pre-movement 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 b/min).

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 noninvasive 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 paralyzed patients.

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The Use of EEG Modifications Due to Motor Imagery for Brain–Computer Interfaces

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***Abstract*—The opening of a communication channel between brain and computer [brain–computer interface (BCI)] is possible by using changes in electroencephalogram (EEG) power spectra related to the imagination of movements. In this paper, we present results obtained by recording EEG during an upper limb motor imagery task in a total of 18 subjects by using low-resolution surface Laplacian, different linear and quadratic classifiers, as well as a variable number of scalp electrodes, from 2 to 26. The results (variable correct classification rate of mental imagery between 75% and 95%) suggest that it is possible to recognize quite reliably ongoing mental movement imagery for BCI applications.**

***Index Terms*—Brain–computer interface (BCI), event-related desynchronizations/synchronization (ERD/ERS), high-resolution electroencephalogram (EEG), motor imagery.**

I. Introduction

The opening of a communication channel between brain and computer [brain–computer interface (BCI)] is possible by using changes in electroencephalogram (EEG) power spectra related to the imagining of movements (see [1] for a review). These EEG variations are specifically detected over centro-parietal scalp areas and can be recognized online by means of linear and nonlinear classifiers [1]–[3], [5]. Scalp potential distribution of EEG power spectra can also be spatially enhanced by using the surface Laplacian (SL) operator [4]. However, a practical desire to use as few scalp electrodes as possible prompted us to investigate low-resolution SL operators in BCI operation. We also explored whether left- and right-motor imagery could be efficiently detected in EEG features gathered from a minimal number of scalp electrodes (two or four) with linear and quadratic classifiers, in a group of normal subjects.

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II. Methodology

A. Experimental Design

At the beginning of a recording session, subjects remained in a resting state—relaxed with eyes opened—for 60 s. The EEG activity of this period was used as a baseline for subsequent analysis of the mental tasks. Subjects were asked to perform two mental tasks, which consisted of imagining the repetitive movement of the right middle finger [right imagination (RI)] as well as that of the left middle finger [left imagination (LI)]. Subjects started the task immediately after the operator instructed them to do so, and they maintained the given task for more than 10 s. During the recording session, the task was executed several times with a resting period of at least 10 s between tasks. After removal of those time segments contaminated by EMG signals (used to monitor arm movements), we retained no less than 180 s of EEG for each task in every subject. This EEG length corresponds on average to the execution of at least 45 trials in each subject recorded. No feedback was furnished to the subjects during the execution of mental tasks. Binary classification between right- and left-motor imagery was used (50% equals to the chance level).

B. EEG Recordings

The EEG potentials were recorded with an extension of the 10/20 international system (26 electrodes). Depending on the study, different subsets of the recording scalp montage were used to select the features to be classified, as described in the following. The EEG sampling rate was 128 Hz. The main operation in the temporal domain was spatial filtering SL, whereby filtered potentials should better represent the cortical activity due only to local sources below the electrodes. We used the Welch periodogram algorithm [6] to estimate the power spectrum of each signal (EEG features). Epochs were 0.5 s long, which gave a frequency resolution of 2 Hz. Only the values inside the frequency band 8–30 Hz were considered for further processing. Thus, an EEG features' sample was represented by 12 n features, where 12 were the spectral components (bins) for each of the n channels used. The periodogram, and, hence, an EEG features' sample, was computed every 0.5 s.

C. Low-Resolution SL

We carried out a simulation study in which simulated potential distributions were generated on a spherical surface by a configuration of current dipoles and sampled with 26 electrodes. We used both theoretical values of the SL, computed analytically as generated by current dipoles, and two estimates of the SL that were obtained by using either all the 26 electrodes (SL) or only nine electrodes (SL9). The computations were performed using the spherical splines estimators [8]. The variable analyzed was the correlation coefficient between the estimated SL distributions (SL and SL9) and the potential distribution (P) on the different electrodes used (10–20 international system).