Current Trends in Graz Brain–Computer Interface (BCI) Research

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***Abstract*—This paper describes a research approach to develop a brain–computer interface (BCI) based on recognition of subject-specific EEG patterns. EEG signals recorded from sensorimotor areas during mental imagination of specific movements are classified on-line and used e.g. for cursor control. In a number of on-line experiments, various methods for EEG feature extraction and classification have been evaluated.**

***Index Terms*—Adaptive autoregressive models, brain–computer interface (BCI), common spatial patterns (CSP), electroencephalogram (EEG) feedback, event-related desynchronization (ERD).**

I. Introduction

The "Graz Brain–Computer Interface" (BCI) project is aimed at developing a technical system that can support communication possibilities for patients with severe neuromuscular disabilities, who are in particular need of gaining reliable control via nonmuscular devices. This BCI system uses oscillatory electroencephalogram (EEG) signals, recorded during specific mental activity, as input and provides a control option by its output. The obtained output signals are presently evaluated for different purposes, such as cursor control, selection of letters or words, or control of prosthesis.

Between 1991 and 2000, the Graz BCI project moved through various stages of prototypes. In the first years, mainly EEG patterns during willful limb movement were used for classification of single EEG trials [1]–[4]. In these experiments, a cursor was moved e.g. to the left, right or downwards, depending on planning of left hand, right hand or foot movement. Extensive off-line analyses have shown that classification accuracy improved, when the input features, such as electrode positions and frequency bands, were optimized in each subject [5]. Apart from studies in healthy volunteers, BCI experiments were also performed in patients, e.g., with an amputated upper limb [6].

It was demonstrated that not only unilateral movement execution [7], [8] but also movement imaging activates primary sensorimotor areas [9], whereby generally a circumscribed "event-related desynchronization" (ERD) is characteristic for the contralateral, and an "event-related synchronization" (ERS) for the ipsilateral hemisphere (see Figs. 1 and 2). This fact is exploited by the Graz BCI system using left–right differences in sensorimotor rhythms to provide a control option in one dimension [10].

II. Methods

A. EEG Feature Extraction

For the analysis of oscillatory EEG components, we investigated the following preprocessing methods:

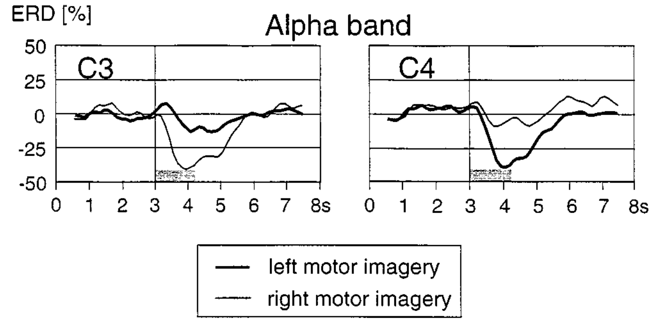

Fig. 1. Grand average ERD curves recorded during motor imagery from the left (C3) and right sensorimotor cortex (C4). The ERD time courses were calculated for the selected bands in the alpha range for 16 subjects. Positive and negative deflections, with respect to baseline (second 0.5 to 2.5), represent a band power increase (ERS) and decrease (ERD), respectively. The gray bar indicates the time period of cue presentation. Modified from Neuper and Pfurtscheller [6].

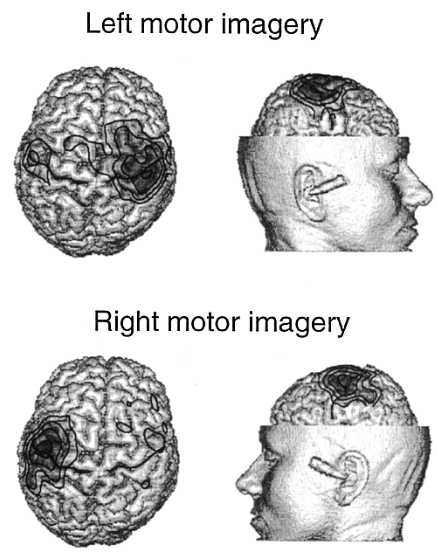

Fig. 2. ERD maps for a single subject calculated for the cortical surface of a realistic head model. The spline surface Laplacian method was applied to the bandpass filtered (9–13 Hz) single-trial EEG data and the distribution of the alpha band ERD was calculated for left and right motor imagery. The spline Laplace maps are shown at $t = 625$ ms after presentation of the cue (arrow in left or right direction). Modified from Neuper and Pfurtscheller [6].

1) calculation of band power in predefined, subject-specific frequency bands in intervals of 250 (500) ms [10];
2) adaptive autoregressive (AAR) parameters estimated for each iteration with the recursive least squares algorithm (RLS) [11];
3) calculation of common spatial filters (CSP) [12].

Band power at each electrode position is estimated by first digitally bandpass filtering the data, squaring each sample and then averaging over several consecutive samples. Before the band power method is used for classification, first the reactive frequency bands must be selected for each subject. This means that data from an initial experiment without feedback are required. Based on these training data, the most relevant frequency components can be determined by using the distinction sensitive learning vector quantization (DSLVQ) algorithm [5], [13]. This method uses a weighted distance function and adjusts the influence of different input features (e.g., frequency components) through supervised learning. When DSLVQ is applied to spectral components of the EEG signals (e.g., in the range from 5 to 30 Hz), weight

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values of individual frequency components according to their relevance for the classification task are obtained.

The AAR parameters, in contrast, are estimated from the EEG signals limited only by the cutoff frequencies, providing a description of the whole EEG signal. Thus, an important advantage of the AAR method is that no *a priori* information about the frequency bands is necessary [14].

For both approaches, two closely spaced bipolar recordings from the left and right sensorimotor cortex were used. In further studies, spatial information from a dense array of electrodes located over central areas was considered to improve the classification accuracy. For this purpose, the CSP method was used to estimate spatial filters that reflect the specific activation of cortical areas during hand movement imagination [15]. Each electrode is weighted according to their importance for the classification. The method makes a decomposition of EEG data into spatial patterns which are extracted from two populations (EEG data during left and right movement imagination) and is based on simultaneous diagonalization of two covariance matrices. The pattern maximizes the difference between left and right population and the only information contained in these patterns is where the variance of the EEG varies most when comparing two conditions. During on-line operation the EEG data is filtered with the most important spatial patterns and the variance of the time series is calculated for several consecutive samples.

B. Classification Procedures

An important step toward real-time processing and feedback presentation is the setup of a subject-specific classifier. For this, two different approaches have been investigated in more detail:

i) neural network based classification, e.g. a learning vector quantization (LVQ) [2];
ii) linear discriminant analysis (LDA) [16], [17].

LVQ was mainly applied to online experiments with delayed feedback presentation. In these experiments, the input features were extracted from a 1-s epoch of EEG recorded during motor imagery. The EEG was filtered in one or two subject-specific frequency bands before calculating four band power estimates, each representing a time interval of 250 ms, per EEG channel and frequency range. Based on these features, the LVQ classifier derived a classification and a measure describing the certainty of this classification, which in turn was provided to the subject as a feedback symbol at the end of each trial [10].

In experiments with continuous feedback based on either AAR parameter estimation or CSP's, a linear discriminant classifier has usually been applied for on-line classification. The AAR parameters of two EEG channels or the variance time series of the CSP's are linearly combined and a time-varying signed distance (TSD) function is calculated [11], [14], [18]. With this method it is possible to indicate the result and the certainty of classification, e.g., by a continuously moving feedback bar.

The different methods of EEG preprocessing and classification have been compared in extended on-line experiments and data analyzes [18], [19]. These experiments were carried out using a newly developed BCI system running in real-time under Windows with a 2, 8, or 64 channel EEG amplifier [20]. The installation of this system, based on a rapid prototyping environment, includes a software package that supports the real-time implementation and testing of different EEG parameter estimation and classification algorithms [18].

III. Experiments

A. Experimental Task

All experiments are based on the same basic imagination paradigm (training session without feedback): At the beginning of each trial ($t = 0.0$ s), a fixation cross appears at the center of a monitor. At 2.0 s a short warning tone ("beep") is delivered and at 3.0 s, an arrow pointing either to the right or to the left (cue stimulus) is presented for 1.25 s indicating the target side of this trial. The subject's task is to imagine a movement of the right or the left hand, depending on the direction of the arrow. One experimental session consists of four experimental runs of 40 trials, providing a total of 160 trials per session.

Further experimental sessions differ mainly with regard to the setup and presentation of feedback. In experiments with delayed feedback, the success of discrimination between imagination of left and right hand movement is provided at the end of each trial ($t = 6.0$ s). In particular, feedback consists of 5 different symbols, indicating how well the subject-specific classifier could recognize the selected EEG features [10].

In the case of an experiment with continuous feedback, a horizontal bar moving to the right or left boundary of the screen is shown for a period of 4.0 s. The subject is instructed to imagine the experience of moving the right hand, in order to extend the bar toward the right side. Concentration on moving the left hand, in contrast, would extend the bar to the left. The length of the bar directly corresponds to the linear distance function obtained by online analysis [21].

B. Protocol

The basic idea of the Graz BCI is to train the computer to recognize and classify certain subject-specific EEG patterns generated by motor imagery. Based on training sessions without feedback, the acquired data are applied off-line to the 1) bandpower, 2) recursive least squares, or 3) common spatial filters (CSP) algorithms, to calculate the appropriate coefficients for each iteration. In other words, a subject-specific classifier is created and then applied to provide feedback in the following sessions. During these feedback sessions, the coefficients are calculated and classified in real-time e.g. to show the feedback bar on the screen. As soon as feedback is provided, however, changes of the EEG patterns can be expected, that require again adaptation of classification methods. There is evidence from several experiments that it is favorable to update the classifier after a few feedback sessions [2], [14], [18], [19].

IV. Results

A. Experiments with Delayed Feedback

Long-term experimental series, using feedback computed with the bandpower and LVQ approach, were carried out with four subjects. This type of feedback yielded to minimum on-line classification errors of around 10, 13, 14, and 17% after several sessions [14].

B. Experiments with Continuous Feedback

In these experiments, the feedback horizontal bar was continuously updated in real-time by using either the CSP or AAR together with LDA approach. After 6 or 7 sessions with several updates of the weight vectors, the lowest on-line errors for three subjects were 1.8, 6.8, and 12.5% for the CSP method [19] and, around 5, 9, and 9% for the AAR method [18].

To compare the classification results obtained with different preprocessing methods, namely, bandpower, RLS, and CSP algorithm, the time courses of error rates were computed with a ten times 10-fold cross validation of a linear discriminant. The ten times 10-fold cross validation mixes the data set randomly and divides it into ten equally sized disjunct partitions. Each partition is then used once for testing, the other partitions are used for training. This results in ten different error rates, which are averaged. This is the error rate of a 10-fold cross validation. To further improve the estimate the procedure is repeated ten times and again all error rates are averaged. Fig. 3 shows the error

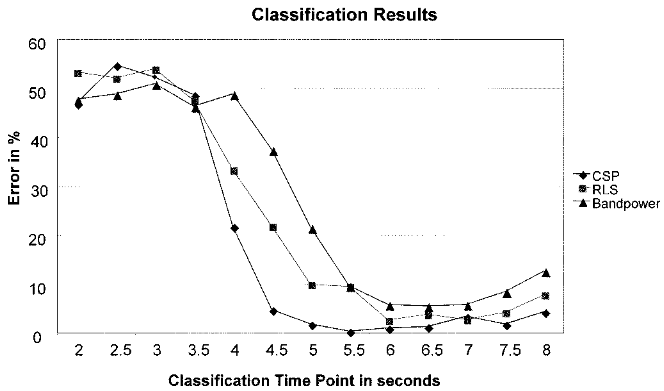

Fig. 3. Classification results for one representative subject and session (consisting of 160 trials) and three different algorithms: (i) CSP, (ii) RLS, and (iii) bandpower. The error rates were obtained with a 10 times 10 fold cross validation of a linear discriminant. The cue stimulus (arrow in left or right direction) was presented from second 3 to 4.25.

time courses for one experimental session of a trained subject. On-line feedback was given with the CSP method. After cue presentation, the error rate decreases significantly for all three algorithms. The lowest error rate for the CSP method (1%) was observed at second 5.5, the lowest error rate for the RLS (3%) at second 6 and for bandpower (6%) at second 6.5. While the lowest error rate differs from subject to subject the differences of the classification results of each method presented in Fig. 3 can be basically seen in all investigated subjects.

V. Discussion

Recent experiments were carried out to optimize the BCI training procedure. Although a direct comparison of experiments with delayed vs. continuous feedback is not possible, it appears that instantaneous feedback information improves the left–right differentiation of EEG patterns [6], [18], [19], [21]. It was shown recently that a visual target stimulus as used in BCI experiments is able to modify sensorimotor rhythms already about 250 ms after target-onset [22].

The classification results show that all methods used, 1) bandpower, 2) AAR, and 3) CSP, result in low classification error rates after some sessions. At this time, the standard method used at our lab is AAR parameter estimation with the RLS, combined with the LDA algorithm. AAR models have the advantage that it is not necessary to specify the reactive frequency band, as it is for the bandpower method.

The linear discriminant analysis has the advantage that, compared to the LVQ, a smaller amount of training trials is needed to set up a suitable classifier for on-line experiments. Therefore, the next experiment can be performed immediately after a session which was used to calculate the classifier.

First investigations with the CSP method reveal promising results. However, one has to consider that this method requires a larger number of electrodes than the other procedures and that it shows some sensitivity to the electrode montage. The CSP method might be an interesting approach for special applications, as e.g. to process signals from implanted electrode arrays.

An important feature of the new Graz-BCI is, that it is equipped with a remote control that allows controlling the system over, e.g., an Internet connection. That means a patient's BCI system can be remotely controlled and the classifier updated if necessary. Furthermore, EEG data recorded during the training sessions at the patient's home can be transmitted and monitored by the BCI developer. At this time the Graz BCI system consisting of a two-channel amplifier and a notebook are used by a tetraplegic patient to control the opening and closing of a hand orthosis. Imagination of feet movement produces a control signal to close the hand and imagination of right hand movement causes an opening of the hand orthosis. After 62 training sessions over a period of five months the patient can perform the task with an accuracy of about 90–100%. The system is installed in the patient's home and remote controlled from our lab over a distance of 50 km.

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The Effects of Self-Movement, Observation, and Imagination on μ Rhythms and Readiness Potentials (RP's): Toward a Brain–Computer Interface (BCI)

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***Abstract*—Current movement-based brain–computer interfaces (BCI's) utilize spontaneous electroencephalogram (EEG) rhythms associated with movement, such as the μ rhythm, or responses time-locked to movements that are averaged across multiple trials, such as the readiness potential (RP), as control signals. In one study, we report that the μ rhythm is not only modulated by the expression of self-generated movement but also by the observation and imagination of movement. In another study, we show that simultaneous self-generated multiple limb movements exhibit properties distinct from those of single limb movements. Identification and classification of these signals with pattern recognition techniques provides the basis for the development of a practical BCI.**

***Index Terms*—Electroencephalogram (EEG), mirror neurons, power spectrum.**

I. Introduction

The concept of a direct interface between the human brain and a sophisticated artificial system, such as a computer, is not a new one. In recent years, there have been advances in a number of fields that make the design and development of a practical brain–computer interface (BCI) possible. Such a BCI would be capable of quickly and reliably extracting meaningful information from the human electroencephalogram (EEG) or other recordable electrical potentials, such as the electromyogram (EMG), electrocardiogram (EKG), etc. Over the past decade, several working BCI systems have been described in the literature [2], [3], [6]–[8]. These systems use a variety of data collection mechanisms, pattern recognition approaches, and interfaces, and require different types of cognitive activity on the part of the user.

One type of BCI that has been examined extensively derives information from a user's movements or the imagination of movement. Many of these *movement-based BCI's* recognize changes in the human μ rhythm, which is an EEG oscillation recorded in the 8–13 Hz range from the central region of the scalp overlying the sensorimotor cortices [4]. This rhythm is large when a subject is at rest, and is known to be blocked or attenuated by self-generated movement. Indeed, the μ wave is hypothesized to represent an "idling" rhythm of motor cortex that is interrupted when movement occurs. The free-running EEG shows characteristic changes in μ-activity, which are unique for the movement of different limbs [9]. These findings have and will continue to be useful in the construction of BCI systems.

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The performance of a movement is also generally accompanied by a readiness potential (RP; also called Bereitshaftspotential or BP) which is most prevalent over cortical motor areas. A similar response can be elicited if the movement is imagined. The RP is a time-locked response to the movement event, or event-related potential (ERP), that is extracted from the ongoing EEG using signal averaging techniques across a number of trials.

The primary goal of the two studies we report was to characterize μ and RP signals in simple, straightforward tasks. The recognition and discrimination of these signals could then provide a basis for the development of a practical BCI, one that would be useful to both normal and disabled individuals.

II. Study 1

In this study, we show that the μ rhythm is significantly attenuated by self-generated movement. Furthermore, some attenuation occurs when a subject *observes* the movement or *imagines* making the same, self-generated movement. According to Rizzolatti and colleagues, the responsiveness of the μ wave to visual input may be the human electrophysiologic analog of a population of neurons in area F5 of the monkey premotor cortex [1], [5]. These mirror neurons respond both when the monkey performs an action and when the monkey observes a similar action made by another monkey or by an experimenter. Other studies have reported that mu-like waves are blocked by thinking about moving [10]. The blocking of the μ rhythm by visual and imagery input may have implications for understanding movement-related responses and for the rehabilitation of movement-related neurological conditions.

III. Methods

Subjects in this study were 17 healthy volunteers (ten men, seven women, ranging in age between 19–58, with a mean of 27.7 years). Most subjects were students or employees at the University of California, San Diego (UCSD) and naive to the purposes of the experiment. Only ten subjects were used for statistical analysis because of problems with noise, such as movement artifact or too much blinking. All subjects signed a consent form that was approved by the UCSD Human Subjects IRB committee.

EEG signals were recorded from 6 sites on an electrode cap placed over frontal (F3, F4), central (C3, C4), and occipital (O1, O2) areas according to the standard 10–20 International Electrode Placement System. Blinks and eye movements were monitored with an electrode in the bony orbit dorsolateral to the right eye. Trials contaminated with eye movement artifact were rejected and not included in the averages. EEG was amplified by a Grass model 7D polygraph using 7P5B preamplifiers with bandpass of 1–35 Hz. For computerized data collection and analysis, the ADAPT (©Vankov, 1997) scientific software was used. EEG was digitized online for two minutes during each condition at a sampling rate of 256 Hz. All electrode sites showed impedance of less than 5 kΩ.

Subjects participated in four conditions:

1) *rest:* in which subjects sat in a comfortable chair inside an acoustic chamber, but no particular task was required;
2) *self-generated movement:* subjects were asked to move their opposing thumb to middle fingers of the right hand (making a "duck" movement);
3) *observation:* subjects watched a confederate of the experimenter perform the "duck" movement;