CURRENT TRENDS IN GRAZ BRAIN-COMPUTER INTERFACE (BCI) RESEARCH

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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 non-muscular devices. This BCI system uses oscillatory 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 1999, 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]. From the preliminary results of the patients' study, we could expect that spatiotemporal EEG patterns related not only to planning but also to imagination of a specific movement, can be classified on-line and therefore used for cursor control.

As mentioned before, scalp-recorded rhythmic EEG components are used as input signal. Several studies have shown that EEG responses during voluntary movement can involve both, "event-related desynchronization" (ERD), and "event-related synchronization" (ERS) of different frequency components [7]. During preparation of a voluntary hand or finger movement, for example, a circumscribed ERD can be found over the contralateral hand area with respect to the side of the movement being planned [8]. Of special interest is that such an asymmetrical ERD distribution could also be demonstrated, when subjects only imagine performing such movements [9]. This fact is exploited by the Graz BCI system using left-right differences in the sensorimotor EEG to provide a control option in one dimension [10].

II. Methods

A. EEG Preprocessing

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

(i) Calculation of band power in predefined, subject-specific frequency bands in intervals of 250 (500) ms [10],
(ii) Adaptive autoregressive (AAR) parameters estimated with each iteration [11],
(iii)Calculation of common spatial filters (CSP) [12].

When band power data are 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 of 5 to 30 Hz), weight 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 cut-off 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 extract a series of spatial filters with decreasing discriminatory power [15]. These spatial filters can be seen as a representation of spatial EEG patterns associated with the different mental states (e.g. left and right motor imagery).

B. Classification Procedures
An important step towards 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], and
(ii) Linear discriminant analysis (LDA) [16, 17].

LVQ was mainly applied to on-line 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 AAR parameter estimation, a linear discriminant classifier has usually been applied for on-line classification. The AAR parameters of two EEG channels 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 analyses [18, 19]. These experiments were carried out using a new developed BCI system running in real-time under Windows with an 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 4 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 (Figure 1). 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 on-line 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 offline to the (i) bandpower, (ii) recursive least squares (RLS) or (iii) 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 4 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 horizontal feedback 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 10 times 10 fold cross validation of a linear discriminant. Figure 2 shows the error 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.

![Classification Results](image)

Figure 2: Classification results for one subject and session for 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 arrow was presented at second 3.

V. Discussion

Recent experiments were carried out to optimize the BCI training procedure. For example, we investigated the impact of feedback presentation on sensorimotor rhythms [22]. 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, 21].

The classification results show that all methods used, (i) bandpower, (ii) AAR and (iii) 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 an analog dial up, LAN or Internet connection. Beside on a normal PC, the system also runs on a
notebook or embedded computer. That means a patient’s system can be remotely updated, to change the weight vector, the analysis method or to install improved software. Furthermore, EEG data recorded during the training sessions at the patient’s home can be transmitted to the BCI developer for off-line processing. At this time a prototype system is tested for opening and closing a hand-orthesis in a patient with a C5 lesion. The system is installed in the patient’s home and remote controlled from our lab.

Another goal of the Graz BCI project is to implement EEG-based control of prosthetic devices to investigate how the feedback (e.g. moving hand prosthesis) affects the overall accuracy of the system. It can be expected that providing feedback by a moving hand prosthesis is more efficient than a cursor moving on a computer monitor.

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