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Brain–Computer Interface—a new communication device for handicapped persons*

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A Brain–Computer Interface (BCI) is a system which can bypass the normal motor output through the spine by using bioelectrical signals recorded on the intact scalp during purely mental activity. Such a BCI must be able to classify EEG patterns on-line and can be used to control, e.g. the movement of a cursor on a monitor. First results on a BCI developed in Graz are reported: 85% correct movements can be obtained after only a few days training.

1. Introduction

Movement is initiated by efferences originating in the motor cortex which are transmitted via the corticospinal tract to the motoneurons of muscles. In patients with lesions of the cervical spine this transfer is affected and movement is impaired or even not possible. In these patients, however, the brain is normally not affected and can demonstrate normal functioning of the motor areas. The idea of a new form of communication device for handicapped persons is to record bioelectrical signals on the intact scalp close to the motor cortex and to use these signals to control a movement.

For realization of such a brain–computer interface (BCI) that allows to bypass the normal motor pathways two prerequisites are necessary:

1. The BCI must be able to distinguish between several patterns of the EEG;
2. Spatio-temporal EEG patterns must be classified on-line, without using averaging techniques, to allow on-line control.

This paper reports on these prerequisites for a simple EEG-based type of BCI and the first steps to design a new prosthetic device.

2. EEG correlate of movement planning

It is known since the work of Jasper and Penfield [1] and Chatrian *et al.* [2] that the EEG displays characteristic changes prior to movement. The mu rhythm of the contralateral central region is desynchronized or blocked about 1 second before movement onset. This movement-related desynchronization (more general: event-related desynchronization = ERD) can be quantified and displayed either for one electrode in form of a time course

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or for one moment in time and multiple electrodes in form of a topographical display or map. ERD time courses and ERD maps visualize movement-related desynchronization of sensorimotor rhythms and give spatio-temporal information about activation of sensorimotor areas during planning and execution of movement.

It has to be kept in mind that the display of ERD maps is based on averaging techniques, that means the movement has to be repeated at least 30 or more times in intervals of some seconds before ERD can be calculated. This technique cannot therefore be used for on-line classification but demonstrates, nevertheless, that different ERD patterns are obtained during planning of right and left hand movement, planning of speech and prior to reading of words (Figure 1). This means that different types of mental activity without any sensory input or motor output result in characteristic ERD maps [3, 4].

3. Classification of non-averaged ERD patterns

The possibility to classify single trial EEG data has been demonstrated recently [5–7]. The data used stem from a movement experiment in which each subject was asked to press a microswitch with the index finger. The hand to be used (left or right) was indicated by a cue stimulus after which the subject had to wait for one second for another stimulus which indicated the start of movement. During this second, the EEG was recorded on 30 electrodes placed on the scalp in the form of a rectangular array at about equidistant intervals. Two electrode positions (C_3, C_4) were equivalent to the international 10–20 system (see Figure 2). The aim of classification was to predict the side of finger movement based on the EEG data recorded in between the two stimuli where the movement planning took place.

3.1 *Feature extraction*

Pattern recognition is a two-stage process consisting of feature extraction and pattern classification. In feature extraction a subset of the measurements available of an experiment is chosen and compiled to a feature vector which is then passed on to the pattern classifier. Obviously the precondition of good classification results lies in creating feature vectors from which the classifier can disambiguously imply to which class the input belongs.

Several kinds of features have been tried for classification of ERD patterns of single trials, starting from simple band power values, which require only squaring of each sample, and going on to more complex methods for finding the envelope of the signal by the Complex Demodulation and the Hilbert Transform. It was found that the Hilbert Transform gives the best results (classification accuracy of about 90%), while band power values (classification accuracy of about 70–80%) are obtained more quickly than the other methods. Both accuracy and speed of feature extraction are important for on-line classification of EEG patterns. Another important aspect is the time interval the feature vector represents. Naturally, the planning phase doesn't always start at exactly the same time after the first cue, depending on the subject's attention, wakefulness and adaptation to the task. For the Hilbert Transform features it has been shown that optimizing the time interval around the minimum envelope value (minimum amplitude meaning maximum event-related desychronization) improves the classification accuracy by 10–15% compared to a fixed time interval starting 0·5 sec after the first cue [8].

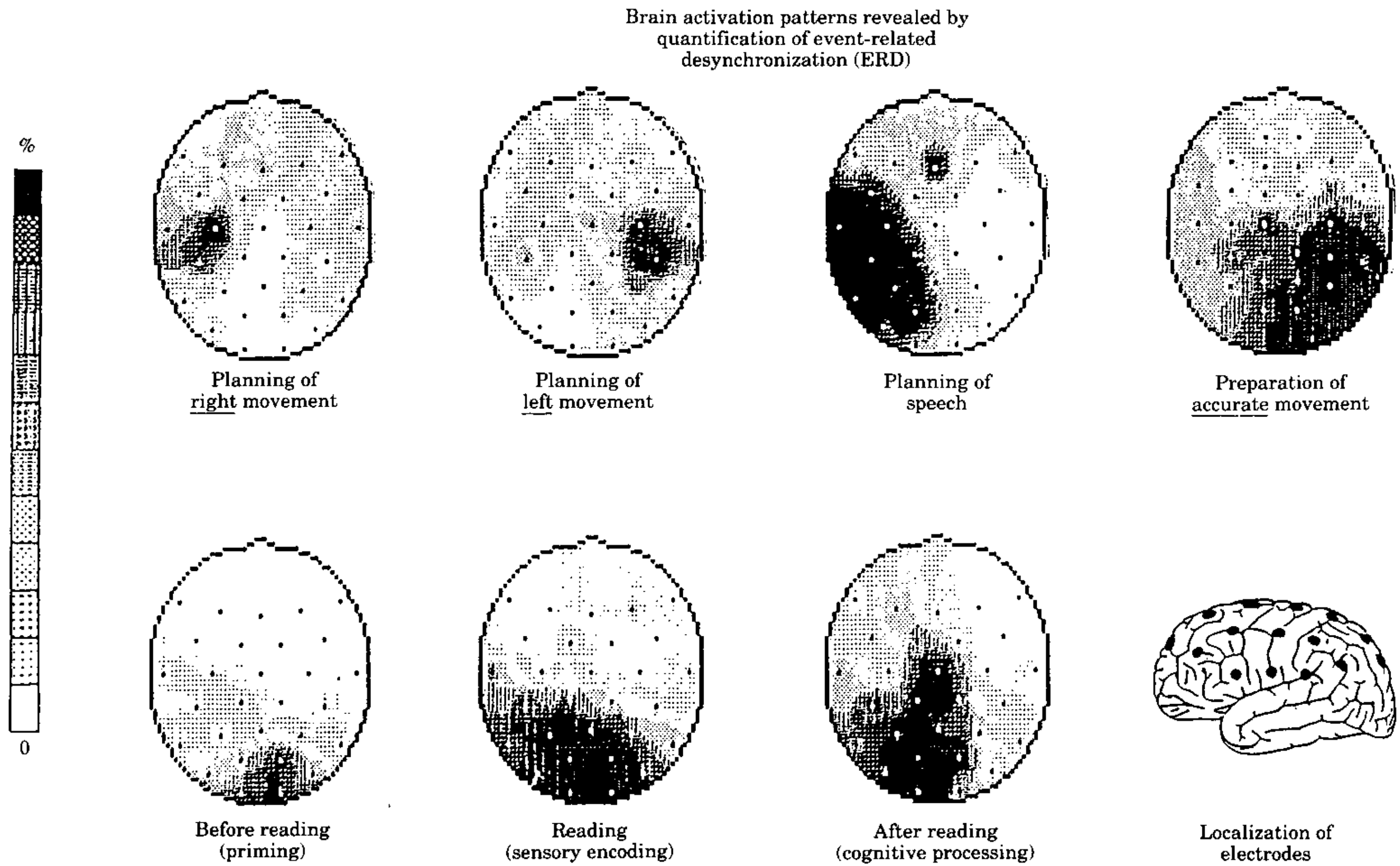

Figure 1. Different types of cortical activation patterns (ERD maps). Each map was obtained by the averaging technique after a great number of repetitions of the individual task (finger movement, speaking, reading). 'Black' marks cortical regions with large ERD and large cortical activation.

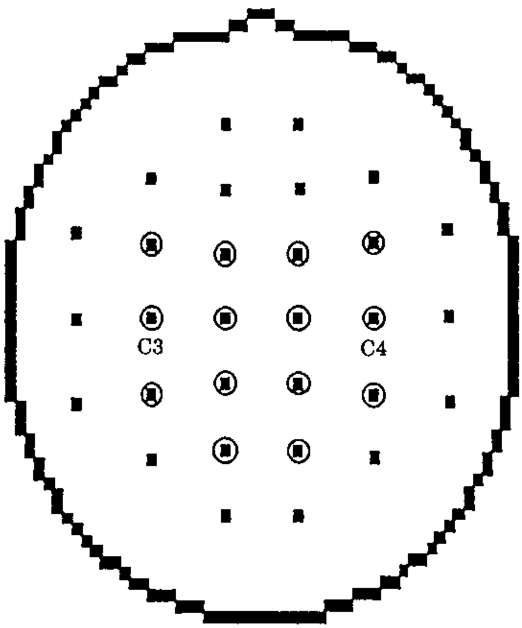

Figure 2. Location of electrodes on the scalp.

For on-line classification such optimizations are not so trivial because (1) the time interval in which the minimum value is to be found is not defined, and (2) segmentation methods which can quantify changes of the EEG are limited by the need to react to changes without much delay, so allowing only very small windows. For the moment the problem was solved by allowing multiple classifications at different, but overlapping, time intervals which are then combined to one decision by majority voting. The more classifications are allowed the more insensitive the system will be to delays of the planning phase because as long as more than one half of the classifications are correct the decision will be correct. On the other hand the number of classifications allowed is limited by the delay of reaction this method causes. Experience has shown that combining the classifications of about half a second is quite a good compromise between speed of reaction and stability of the decision output (flickering of the controlled cursor will disturb the user more than the prompt reaction of the system will please him).

3.2 *Pattern classification*

Several types of classifiers have been tested with EEG data: Artificial Neural Networks, such as the Multi-Layer Perceptron [9], Partially Recurrent Network [10] and Cascade Correlation Network [11], and Machine Learning Methods, such as the Learning Vector Quantizer [12]. No clear preference could be established by testing these classifiers on the EEG data described above. It seems as though the type of classifier is not as important for classification accuracy as the feature extraction method. Nevertheless, the Learning Vector Quantizer was chosen for the Graz BCI because of its simplicity, its speed of training and its fairness to the existing classes. By fairness we mean that the Learning Vector Quantizer tries to divide the classification error evenly on the existing classes, while e.g. for the Multi-Layer Perceptron a preference for one class was observed.

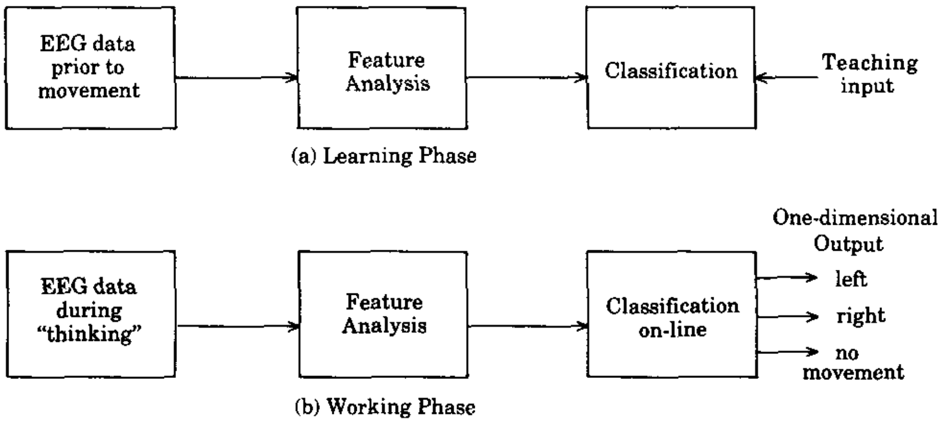

Figure 3. Outline of the Graz BCI for one-dimensional movements.

4. Layout of the Graz BCI

The one-dimensional Graz BCI consists of two components: the processing part where the feature extraction takes place and the classification part (see Figure 3). The classifier has to be trained for each user individually to distinguish between two kinds of patterns, here the EEG during planning of left and right finger movements. This is done by an experiment similar to the one described in section 2 and using the EEG data during the movement planning phase to teach the classifer what planning of left and right finger movements looks like for this specific user. After this the user can control a cursor by merely going through the planning phase of either left or right finger movement without actual motor output.

At the moment the features used for classification consist of power values calculated from two electrode positions (C_3 and C_4, see Figure 2) and the Learning Vector Quantizer is used as the classifier. Five time-points are concatenated to one feature vector which is then presented to the Learning Vector Quantizer. Because the planning phase in each trial starts at a slightly different time-point, five such classifications are always performed, the results of which are combined to one decision by majority voting. The exact time interval which is used for classification is defined by the paradigm shown in Figure 4. It starts with the presentation of the target and ends at the presentation of the cursor (cue) whose movement is determined by the decision rule stated above and shown to the user via feedback. The number of decisions made during one trial therefore depends on the time between the target and the cue which was fixed to one second to allow only one decision per trial, which made the cursor jump right into the target.

A very similar experiment was already performed by Wolpaw *et al.* [13] (New York BCI) where users also moved a cursor into a target. The main difference between the New York BCI and the Graz BCI is that in New York the users had to adapt themselves to the system over several weeks while in Graz the system adapts to the users which reduced the time for reasonable results from weeks to some days. A further difference between the two BCI prototypes is that the New York BCI is internal-paced and unspecific while the Graz BCI is external-paced and specific. Internal-paced here means that the subject determines the start of 'mental activity' himself while in the external-

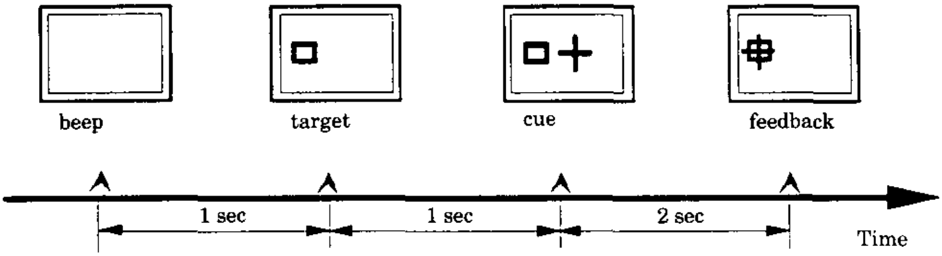

Figure 4. Working phase of the Graz BCI.

paced system in Graz a stimulus is given (target, see Figure 4) to indicate when the 'mental activity' should start. The term 'specific' is used here to indicate that in the Graz BCI the EEG is recorded over specific cortical areas, the motor and premotor areas, which are known to be involved in motor processing. In this sense the New York BCI uses 'unspecific' electrode locations because some undefined mental process is used to control the movement.

First tests were made in one subject. Using the band power samples, the performance of the Graz BCI after four sessions of about half an hour each reached over 85% correct movements (31 out of 35 left movements and 36 out of 45 right movements predicted correctly), the initial performance after the Learning Phase having been about 70%. Both the biofeedback and the updating of the classifier in between the sessions using the new data helped to increase the accuracy significantly.

For further improvement of the BCI and its extension to two or more dimensions, optimization of the various parameters is very important. This starts with the necessary number of electrodes and their location on the scalp, includes the problem of EEG data transformation to obtain reference-independent data and to improve the spatial resolution, the processing of EEG signals by different analyzing methods and ends with the selection of the best classifier.

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