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Graz-BCI: State of the Art and Clinical Applications

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***Abstract*—The Graz-brain–computer interface (BCI) is a cue-based system using the imagery of motor action as the appropriate mental task. Relevant clinical applications of BCI-based systems for control of a virtual keyboard device and operations of a hand orthosis are reported. Additionally, it is demonstrated how information transfer rates of 17 b/min can be acquired by real time classification of oscillatory activity.**

***Index Terms*—Brain–computer interface (BCI), event-related desynchronization/synchronization (ERD/ERS), motor imagery, rehabilitation, sensorimotor rhythms, virtual keyboard.**

I. Introduction

Currently available brain–computer interfaces (BCIs) can be grouped according to the kind of brain signals they process or the mode of operation they depend on. Within brain signals, we can, for example, differentiate between evoked potentials (EPs), slow cortical potential shifts, and oscillatory electroencephalogram (EEG) components. There are two main categories of mode-of-operation implemented by BCI systems. Within the first category, brain signals are analyzed in cue- or stimulus-triggered time windows either by identifying changes in EPs [1] and slow cortical potentials shifts [2], or quantifying oscillatory EEG components [3], [4]. These types of BCIs, operating with predefined time windows, are generally gathered under the term "cue-based" or "synchronous" BCI systems. Within the second category, a continuous analysis of brain signals is performed either with the purpose of detecting event-related potentials or transient changes in oscillatory EEG components. This type of BCI operates in an asynchronous mode. These are "noncue-based" or "asynchronous" BCI systems and, therefore, have been referred to as "asynchronous detectors" in as much as they operate on the basis of movement-related potentials [5], [6].

In the last decade, work on the Graz-BCI has focused predominately on characterizing and differentiating two or more brain states or EEG patterns, respectively, associated with motor imagery in predefined time windows (cue-based or synchronous BCI). Our research has been focused on methods of parameter estimation and on testing a considerable number of classifiers [7]–[9]. The currently implemented discrimination method is capable of differentiating between two brain states associated, in our case, with two different types of motor imagery in defined time windows. It can achieve classification accuracies from 80% up to 100% [4]. The neurophysiological basis for the Graz-BCI is the fact that actual performance of a limb movement and the imagination of the same movement activates similar cortical areas, as abundantly demonstrated by functional magnetic resonance imaging (fMRI) [10] and positron emission tomography (PET) investigations [11]. Similarly, the quantification of sensorimotor rhythms has shown that the spatiotemporal patterns of event-related

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desynchronization (ERD) are very similar during actual movement performance and imagination of respective limb (hand or foot) movements [12]. In the following sections, four projects are described in some detail, including the development of: 1) a "virtual keyboard" (VK) controlled by oscillatory EEG signals; 2) a BCI-based operation of a hand orthosis applied by a tetraplegic patient; 3) performance of long-term BCI training of a patient by means of telesupport; and finally, 4) probing the limits of information transfer characterizing the application of the Graz-BCI.

II. Virtual Keyboard Controlled by EEG

Synchronous BCI systems can be used to operate a spelling device or a virtual keyboard. Recently, Birbaumer *et al.* reported [2] on a spelling system utilized by three patients [all affected by amyotrophic lateral sclerosis (ALS)] that rests on slow cortical potentials. Two of the three patients achieved a classification accuracy of 70%–80%, which enabled them to achieve a spelling rate of approximately 0.5 letters/min. In contrast to the method applied by Birbaumer *et al.*, we chose oscillatory EEG components as input signals for the BCI and studied the spelling rate in three able-bodied subjects while operating a VK [13]. For this reason, the signals from two bipolar EEG channels were separated in subject-specific alpha and beta bands and subsequently analyzed during the performance of two types of motor imagery. Each subject used different motor imagery strategies, i.e., right versus left hand, right hand versus tongue, and left hand versus foot. Two hidden Markov models (HMM), one for each type of motor imagery, were trained by the trials resulting from the training session. The appropriate classification of the ongoing EEG was then performed by selection of the class with maximal probability achieved by the respective HMM-model [7]. The required spelling process consisted of the selection of one particular letter out of the whole alphabet through successive steps of isolation. The overall structure of our VK contains five consecutive levels of selection and two further levels of confirmation and correction. The subject's goal was to write the phrase "VIRTUAL KEYBOARD." The three subjects achieved spelling rates of 0.85, 1.02, and 0.67 letters/min, respectively. These values correspond approximately to seven decisions per minute. Generally, there are several complementary ways to increase the number of letters spelled per minute: 1) shortening the trial length and, thereby, the time between two imaginations (currently, this interval lasts for 8 s); 2) expanding the number of movement types to be imagined ($n > 2$); 3) considering the probability rate of the occurrence of specific letters.

A newly developed VK, called the VK-T8, is based on a dictionary developed for use with cell phones using T9 technology [14]. The VK-T8 has eight buttons, six of eight buttons represent four letters, i.e., the first button refers to "A, B, C, D," the second to "E, F, G, H." In contrast, the next to last button represents "Y, Z", and finally, the last button represents only the symbol ".". Each button is also associated with a specific number, so that each word within the wordlist is numerically coded. Accordingly, the German word "KAUFEN" ("BUY") can also be expressed by the number code "316 224". The wordlist is comprised of 145 words that are expected to be useful for basic communication. Ultimately, the VK-T8 system uses four steps to select a letter. To determine the theoretical average spelling rate characterizing the use of the VK-T8 BCI system, the selection of 40 randomly chosen words was simulated under the assumption of 100% correct decisions and based on a trial length of 7.5 s. The resulting theoretical spelling rate for the BCI-VK-T8 was in average 2.73 ($\mathrm{SD} = 0.94$) letters/min. In a first study, three subjects were instructed to write five predefined words using the VK-T8 system. The achieved spelling rate varied from 1.06 to 4.24 letters/min. However, it should be underlined that the spelling rates of the VK-T8 directly depend on the amount of entries in the wordlist which was limited to 145 words in the current experimental setup. A general problem using of a VK controlled by a BCI is the relation between the required decisions per letter and the classification accuracy reached by the BCI. Some illustrative examples are given in Table I.

TABLE I
Probability of Correct Letter Selection Dependent on Changing Classification Accuracies

	accuracy				
dec./letter	0.80	0.90	0.95	0.99	
6	0.26	0.53	0.74	0.94	standard VK
5	0.33	0.59	0.77	0.95	
4	0.41	0.66	0.81	0.96	VK-T8
3	0.51	0.73	0.86	0.97	
	probability of correct letter				

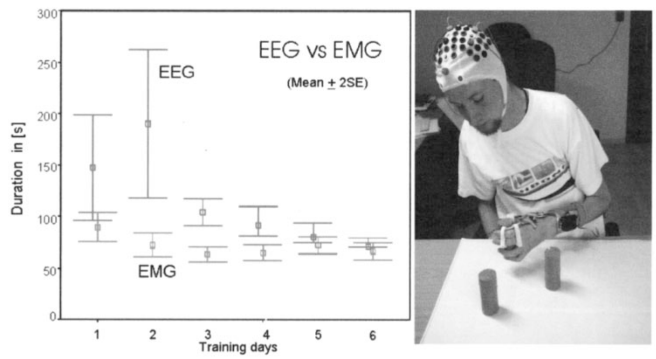

Fig. 1. Operation times (for seven operations, i.e., opening/closing the orthosis) for six consecutive training days comparing EEG and EMG used for inspection. After six days the performance is about the same (about 6 operations/min) with EEG and EMG.

Using the standard VK, the theoretical probability of typing the correct character is 53% (with six decisions/letter and an accuracy of 90%). Using the VK-T8 (with four decisions/letter) resulted in a value of 66%. The probability of typing the correct character increases as the number of decisions per letter decreases or accuracy on the BCI increases. Correspondingly, future work is focused on developing "intelligent" VKs by improving the classification accuracy of the BCI system to reach an optimal performance.

III. BCI-Based Manipulation of Hand Orthosis

In a pilot project with a tetraplegic patient, a mechanical-hand orthosis was controlled by ongoing EEG activity based on a synchronous BCI design and two types of motor imagery (Fig. 1). After a number of training sessions with varying types of motor imagery strategies over a period of several months, motor imagery of foot movement versus right hand movement achieved a classification accuracy of close to 100% [15].

The inspection of the EEG signals revealed that foot motor imagery induced long trains of 17-Hz beta oscillations focused on the electrode position near the vertex (Cz). The assumed underlying processes may be conceptualized as follows: by repetitive imaginations of foot movement, the oscillatory behavior of neuronal networks close to the foot representation and/or supplementary motor areas, both localized near to the midcentral electrode position (Cz), is modified and, therefore, reinforces the generation of activity in the beta band. This concept underlines the necessary application of repeated BCI-sessions associated with feedback to the subject on the one side, and at the same time making use of the plasticity of the brain on the other side [15]. Coming

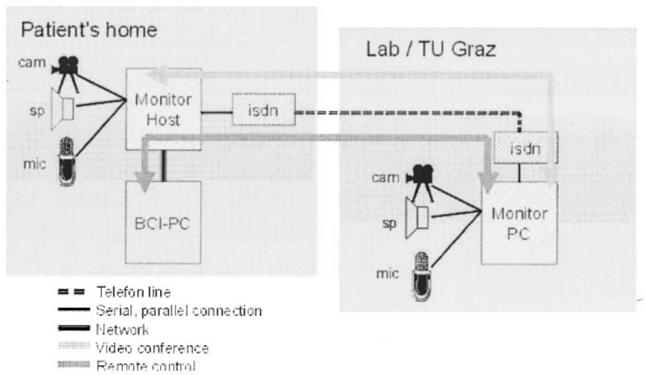

Fig. 2. Schematic model of the telemonitoring system. At the right, there is the Monitor PC placed at our lab by which the BCI is controlled. The left side represents a rough schema of the BCI system (BCI-PC) and a multimedia PC used for video conferences with patient and caretaker. Double arrow (light grey) symbolizes the connection needed for the video conference. The other double arrow (black) depicts the connection the remote control is based on.

to our concrete application, by using mentally-induced 17-Hz oscillations as a simple brain switch, a hand orthosis was constructed that can operate in an asynchronous mode. After a training period of six days, the patient was able to perform about six opening/closing operations in 1 min (Fig. 1).

IV. BCI Training of a Patient via Telesupport

BCI training requires continual interaction between the patient using the BCI and an expert familiar with the system and can go on for weeks or even months. A patient's BCI training can take place under three conditions: 1) the patient stays at home and a BCI expert is there to assist him or her during the performance of the BCI training; 2) the patient has to be present in the laboratory during the required training sessions; and, finally, 3) the patient stays at home and participates in BCI training via a remote control system managed from the laboratory (as described beyond). Our telemonitoring system includes a remote-control function connecting the patient and his or her caretaker on the one side with the BCI instructor on the other. The BCI is controlled on-site by direct access to the system, whereby new paradigms can be created, adjusted, or simply recompiled. Observing the flow of paradigms and a parallel projection of the patient on a video monitor provides direct impressions to the supervisor concerning important technical and social aspects of training. If new aspects emerge in the course of the session, the respective EEG data can be transferred to the laboratory, be analyzed there, and subsequently results can be used to make immediate changes in the ongoing running paradigm during the same session. The connection between the systems is performed on the basis of an ISDN telephone line [16] (Fig. 2).

The system described previously is currently in use by a completely paralyzed patient (K., aged 32 yrs) who lives in Bad Kreuznach (Germany). He was trained to use the BCI system and to exert control on a corresponding VK. By adapting our standard BCI paradigm [4], starting with simple feedback training, the patient learned to control the classifier based BCI system. Subsequently, the VK device was introduced. At the beginning of the training with the VK, the patient had to select one out of two letters, in subsequent sessions the number of letters was increased stepwise up to eight symbols. "Copy spelling" of short words was performed with a rate of approximately 1 letter/min [17]. More details of the applied VK are reported in [16]. These system features together made it possible to train a patient at a great distance from our laboratory as intensively and as frequently as a patient who had personal contact with the supervisor. This has increased the number of patients applying for and under consideration for BCI. In conclusion, we have successfully demonstrated that a BCI used with a telemonitoring system offers all the crucial functions needed to perform a successful BCI training in distance from the laboratory.

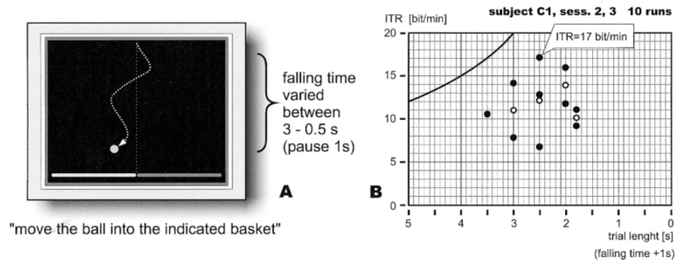

Fig. 3. "Basket-paradigm." (a) The subject has to direct the ball to the indicated goal ("basket"). The trial length varied across the different runs. (b) ITR for subject C1 in relation to trial length is depicted. The black line represents the maximum possible ITR for an error-free classification. (● . . . single runs, ○ . . . averages for specific trial lengths).

V. Limits of Information Transfer Studied in Paraplegic Patients

In this study, two different types of motor imagery (movement of the right versus left hand and movement of the right hand versus both feet) were classified by processing the signals of two bipolar EEG-channels. Over the course of some weeks, four young paraplegic patients learned to control the BCI device [18]. The challenge was to find a minimal trial length enabling a maximum information transfer rate [19]. The two EEG-channels were recorded using gold disk electrodes located 2.5 cm anterior and posterior to electrode positions C3 and C4, respectively. For each EEG channel two features were extracted by computing the natural logarithm of band-power values of the 10–12-Hz alpha band and the 16–24-Hz beta band. Classification of training data (offline) was performed by linear discriminant analysis (LDA). Classifiers, i.e. LDA-weight vectors, were computed and proofed by a 10×10-cross validation for every 0.5 s of the trials. The best classifiers were then used in online feedback sessions. These feedback-sessions used the so-called basket-paradigm [see Fig. 3(a)]. In this paradigm, the patient watches a black screen that is divided in half vertically by a dotted line. There is one red and one green basket at the bottom of the screen. After a pause with a fixed length of 1 s, a red "ball" appears at the top of the screen. The red ball moves down the screen with a constant speed. The speed of the ball, expressed by the time the ball took to travel from the top to the bottom of the screen, varied from run to run. The subject's task was to put the downwardly moving ball in the red basket, which changed sides randomly across trials. The horizontal position of the ball was directly controlled by the BCI-classification output signal. This signal was weighted by offline-calculated gain factors to lead the mean deflection for each direction to the middle of the basket. Each run consisted of 40 trials and trial length varied from 5 to 1.5 s per complete trial. In the latter case, the patients had only 0.5 s of feedback to hit the correct basket.

Three out of four subjects participating in this study achieved promising results after a few runs [see Table II, subject C1 in Fig. 3(b)]. Analysis of their last two experimental sessions (between 10 and 16 runs) revealed that the trial length can be reduced to values of around 2 s, thus providing the maximum information transfer. Accessible information transfer rates (ITRs) reached values between 5 and 17 b/min depending on the subject's performance and mental shape. Table II shows the results gathered for all participants in the experiment described previously.

TABLE II
SUMMARIZED RESULTS OBTAINED BY ALL SUBJECTS. THE "OFFLINE ERROR" REPRESENTS THE CLASSIFICATION ERROR OF THE BEST TRAINING RUN (ESTIMATED BY 10×10-CROSS-VALIDATION). THESE CLASSIFIERS WERE SUBSEQUENTLY USED FOR THE "BASKET-PARADIGM"

subject	age/sex	offline error	max. ITR	trial length
C1	19 / male	5	17.2 bit/min	2.5 s
M1	23 / male	23	3.0 bit/min	3 s
M2	22 / male	16	8.4 bit/min	2 s
M3	27 / male	15	9.3 bit/min	1.8 s

VI. CONCLUSION

A number of studies on the Graz-BCI has shown that motor imagery is a suitable task to operate a BCI system in able-bodied subjects as well as in patients [4], [15], [17]. Of special interest is that the repetition of hundreds of imagery tasks over a period of some weeks/months can induce beta oscillation of a very stable frequency (see Section III). The occurrence of these oscillations can be used as a simple brain switch. This phenomenon underlines the plasticity of the brain and the important role of training- and feedback sessions in establishing new circuitries in the cortex capable of generating beta oscillations.

The information transfer rate defined in bits per minute strongly depends on the classification accuracy and the trial length in a synchronous BCI system. In a study with patients in a rehabilitation center (see Section V) trial length was successively reduced to 2 s. Theoretically, this implies that without any error an information transfer rate of 30 b/min could be realized. It is important to note that under this approach, all training and feedback sessions were organized as a kind of game ("basket game") and therefore, the engagement and attention of the participants was kept high during the experiment [18]. More patients with locked-in syndrome may benefit from the application of BCI-based spelling systems, if the tele-support concept is widely introduced. The feasibility and reliability of such a concept was demonstrated recently between our laboratory at the Graz University of Technology and a patient in Germany at a distance of about 700 km (see Section IV).

At the moment, we are working on a "noncue-based" BCI with the goal to detect specific brain states associated with mental activity in the ongoing EEG signals in real time. In some preliminary experiments, we analyzed 10 min of EEG recorded during 60 self-paced finger movements and obtained a HF difference of 77% [the HF difference results from a subtraction, whereby the false positive rate (FPR) is subtracted from the true positive rate (TPR)] [6]. In the case of self-paced foot movements, an HF difference of 85% could be obtained [20]. These results are very promising and demonstrate that prediction of movement execution can be revealed not only by analyzing movement-related potentials [5], [6], but also by considering the dynamics of oscillatory brain activity.

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