How Many People are Able to Operate an EEG-Based Brain-Computer Interface (BCI)?

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***Abstract*—Ninety-nine healthy people participated in a brain–computer interface (BCI) field study conducted at an exposition held in Graz, Austria. Each subject spent 20–30 min on a two-session BCI investigation. The first session consisted of 40 trials conducted without feedback. Then, a subject-specific classifier was set up to provide the subject with feedback, and the second session—40 trials in which the subject had to control a horizontal bar on a computer screen—was conducted. Subjects were instructed to imagine a right-hand movement or a foot movement after a cue stimulus depending on the direction of an arrow. Bipolar electrodes were mounted over the right-hand representation area and over the foot representation area. Classification results achieved with 1) an adaptive autoregressive model (39 subjects) and 2) band power estimation (60 subjects) are presented. Roughly 93% of the subjects were able to achieve classification accuracy above 60% after two sessions of training.**

***Index Terms*—Brain–computer interface (BCI), electroencephalogram (EEG), event-related desynchronization (ERD), motor imagery, rehabilitation.**

I. Introduction

An electroencephalogram (EEG)-based brain–computer interface (BCI) creates a new communication channel between the human brain and the computer [1]–[3]. This channel may provide patients who suffer from severe motor impairments (e.g. late-stage amyotrophic lateral sclerosis (ALS), severe cerebral palsy, head trauma, and spinal injuries) with an alternative form of communication, where the interaction between brain and computer is realized in real time.

Currently, more than 20 laboratories are working on communication channels between the brain and the computer [4], exploring possible BCI input signals that include evoked potentials [5], slow cortical potentials (SCPs) [6], and oscillatory components [3], [7], [8]. Most studies have been conducted with small subject populations (1–13), and data have mainly been used to develop systems that are highly optimized to the subjects participating in the studies. Subjects' ability to control a BCI vary greatly, however, and some subjects have been excluded from further investigation due to their inability to control the BCI in early training [4].

One of the most successful BCI strategies relies on the subjects' ability to learn to alter the mu and central-beta components of the EEG at will. This method has resulted in accuracies of 80%–95% for one-dimensional (1-D) cursor-control tasks. Wolpaw and McFarland have shown that healthy subjects and spinal-cord-injury patients usually need several months to develop high-accuracy cursor control (i.e.,$>$ 90%) using mu- and beta-frequency components [2], [7]. Birbaumer's group also reports that healthy patients require a training period of several months to achieve accuracies of 65%–80% using slow cortical potentials in a 1-D cursor-control task [9]. Some ALS patients have been trained for more than a year [6]. Each of these methods requires training over weeks or months.

Another approach relying on similar components, the Graz BCI, requires the computer system to "learn" to detect distinct EEG patterns related to the imagination of movement based on EEG recordings over the respective sensorimotor areas. When utilizing two bipolar recordings and either band power or adaptive autoregressive parameters, a single EEG trial classification accuracy of 80%–97% can be achieved after approximately 6–10 20-min sessions [3], [10], [11].

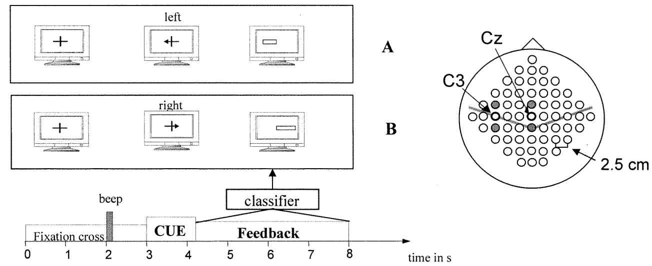

Fig. 1. Panels A and B and the left side show the timing of the experimental paradigm for right hand and feet movement imagery. Fig. 1, right side shows the electrode positions (C3 and Cz in the international 10/20 system) for EEG measurements. The head is viewed from above and the nose points to the top of the page.

To improve the usefulness of BCI methods, researchers must address issues of user-acceptance and training methodology. Reduction in the total number of electrodes necessary to operate a BCI and the length of training time should significantly improve the rate of user acceptance and the general usefulness of BCI methods. We set out to investigate these issues with a large group outside the laboratory. Of interest was how many people at a public exhibition would be able to operate an EEG-based BCI after only 20–30 min of training with only two bipolar EEG derivations. In the same large data set, we compared the performance of a BCI using adaptive autoregressive parameter estimation to band-power estimation. It must be emphasized, however, that the short training period precludes the subject from finding the best mental strategy to control the BCI system. Hence, in this case, it is the system that adapts to the subjects' EEG patterns and not the other way around.

II. Experimental Paradigm

A total of 99 people $(\text{mean age} = 38 \pm 22.4 \text{ yr})$ participated in the experiment. The subjects were free of medication and central nervous system abnormalities and had no prior experience with EEG-based communication systems. The experiments were performed over two months.

The BCI requires EEG trials recorded during two different types of motor imagery. Based on experiences from previous investigations with healthy volunteers, the subjects were asked to concentrate on right-hand versus both-feet movement, which was expected to yield distinct EEG patterns over the sensorimotor regions. The timing of one trial is shown in Fig. 1.

The subjects sat in a comfortable armchair 150 cm in front of a computer screen and were instructed not to move and to keep both arms and feet relaxed. The experiments started with the display of a fixation cross in the center of a screen. After 2 s, a warning stimulus was given in the form of a "beep." After 3 s, an arrow (cue stimulus) pointing to the left or right was shown for 1.25 s. The subjects were instructed to imagine a right-hand movement or a both-feet movement until the end of the trial, depending on the direction of the arrow. In sessions with feedback, the EEG patterns were detected and classified online throughout the session. For 3.75 s after the arrow disappeared, between second 4.25 and second 8, the classification result was used to give a continuously updated feedback stimulus in form of a horizontal bar that appeared in the center of the screen. If the person imagined a both-feet movement, the bar—varying in length—extended to the left, as shown in Fig. 1 (A). If the subject imagined a right-hand movement, the bar extended to the right, as shown in Fig. 1 (B) (correct classification assumed). During this time period, the subjects' task was to extend the bar toward the left or right edge of the screen.

One trial lasted 8 s and the time between two trials was randomized in a range of 0.5–2.5 s to avoid adaptation. All 99 subjects performed one session without feedback, and most of them (94) also performed one session with feedback. Each session consisted of 40 trials with randomized cue direction (20 arrows pointing to the left and 20 to the right). The whole experiment lasted about 20–30 min including electrode application, breaks between sessions, and all settings for the experiment.

III. Methods

The EEG was recorded with gold electrodes from two bipolar channels over the right-hand and foot representation areas (2.5-cm anterior and 2.5-cm posterior to electrode positions C3 and Cz of the international 10/20 electrode system) as shown in Fig. 1 (right side). The EEG signals were amplified and band-pass filtered between 0.5 and 30 Hz and sampled at 128 Hz. For the analysis of the EEG patterns, 1) an adaptive autoregressive (AAR) model (first month) and 2) band power estimation (second month) were applied.

An AAR model describes the time-varying characteristics of the EEG. With only a small number of AAR parameters (in this case six), the spectral EEG-signal properties can be monitored, and the parameters can be used to classify the EEG patterns. AAR parameters were estimated with the recursive-least-squares (RLS) algorithm [11], [12].

For band-power estimation, the average power in the alpha and beta band at each electrode position was estimated by 1) digitally band-pass filtering the data in standard frequency ranges of 10–12 Hz (alpha) and 16–20 Hz (beta), 2) squaring each sample, and 3) averaging over several consecutive samples [3]. A total of 128 samples were averaged, yielding an estimation of the band power for a 1-s interval.

In both cases, linear discriminant analysis (LDA) was used for the classification of the parameters [13]. An LDA weights each input parameter according to its importance. The classification result, the sum of weighted parameters, indicates the class to which the input belongs by the sign of the result. The confidence that can be placed in the class assignment is given by the magnitude of the result.

IV. Processing Environment

The experiments were carried out using a newly developed BCI system running in real time under Windows with a two-channel EEG amplifier [11]. After amplification (g.BSamp), the signals were passed to a laptop computer for data acquisition, processing, visualization, and storage, as shown in Fig. 2. A stimulation unit (g.STIMunit) controls experimental paradigms while a real-time processing system (g.Rtsys) performs the data acquisition, real-time parameter extraction, and classification of the EEG.

The system provides algorithms for offline analysis and allows integrating the same algorithms for real-time processing. A key feature is the rapid prototyping environment that enables fast and easy implementation of different processing algorithms and classification methods for optimizing the BCI performance. The system enables us to achieve reliable results in an early stage of design both for development of the BCI itself as well as for the adaptation of the system to the specific needs of subjects/patients. The environment allows the integration of user-specific hardware and processing modules and gives access to MATLAB and SIMULINK—Toolboxes (MathWorks Inc., Natick, MA) to accelerate the BCI research.

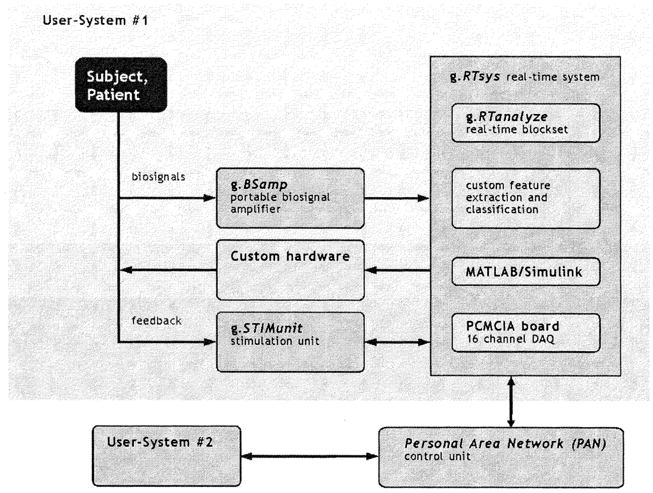

Fig. 2. Depicts the hardware and software architecture of the portable BCI system. Subject's EEG is amplified with g.Bsamp, then digitized and processed in real-time with g.Rtsys. The classified EEG patterns are fed back to the subject based on g.STIMunit. The BCI user-system #1 can be connected via personal area network or internet to other BCI user systems.

The tight coupling between the online experiments and offline analysis of the acquired data is one of the major advantages of the new BCI system, particularly for building the classifier. There were two types of recording sessions: in one type, data were collected to establish a subject-specific weight vector, and in the other type, the subject-specific weight vector was used to classify the EEG online while the subject imagined the requested kind of movement.

In session one, the paradigm, described in Fig. 1 but without feedback, was presented to obtain the subject-specific weight vector. The acquired data were then used offline to 1) estimate AAR model parameters or to 2) estimate the band power. To obtain a more general view of the classification ability, a 10×10 fold cross validation of a linear discriminant was also performed. This validation mixes the data set randomly and divides it into ten equally sized disjunctive partitions. Each partition is then used once for testing, whereas the other partitions are used for training. The resulting ten different error rates are averaged yielding an overall error. To further improve the estimate the procedure is repeated ten times and again all error rates are averaged.

The 1) AAR- or 2) band-power coefficients of the classification time points with the lowest classification error were used to set up the subject-specific weight vectors with the LDA for the following sessions with feedback. This offline procedure, beginning from reading the recorded data from hard disk until the availability of the new weight vector, requires approximately 2 min. Therefore, the next session can be started after only a short break.

In session two, the outputs of the algorithms were calculated and classified with the weight vector in real time to show the feedback online in form of a bar on the screen. The bar, varying in length, pointed to the left if the output of the linear classification was positive and to the right if it was negative. The size of the bar was determined by the absolute value of the classification result, which represents a measure of how reliable the side was determined.

V. Results

It is interesting that in about 20% of the sessions (about 20% of subjects), the two brain states were distinguished with an accuracy of greater than 80% after only 20–30 min of training, as shown in Table I. Further, 70% of the sessions were classified with an accuracy

TABLE I
PERCENTAGE OF SESSIONS WHICH WERE CLASSIFIED WITH A CERTAIN ACCURACY FOR RLS ALGORITHM AND BAND POWER (BP) ESTIMATION. N SPECIFIES THE NUMBER OF SESSIONS.RLS + BP SHOWS THE RESULTS FOR BOTH ALGORITHMS

Classification Accuracy in %	RLS Percentage of Sessions (N=76)	BP Percentage of Sessions (N=117)	RLS+BP Percentage of Sessions (N=193)
90-100	6.6	6.0	6.2
80-89	10.5	14.5	13.0
70-79	30.3	33.3	32.1
60-69	40.8	42.7	42.0
50-59	11.8	3.5	6.7
	100	100	100

TABLE II
PERCENTAGE OF SESSIONS WHICH WERE CLASSIFIED WITH A CERTAIN ACCURACY FOR RLS ALGORITHM AND BP ESTIMATION. N SPECIFIES THE NUMBER OF SESSIONS. RLS + BP SHOWS THE RESULTS FOR BOTH ALGORITHMS

Classification Accuracy in %	RLS		BP	
	Percentage of Sessions S1 (N=39)	Percentage of Sessions S2 (N=37)	Percentage of Sessions S1 (N=60)	Percentage of Sessions S2 (N=57)
90-100	10.3	4.1	8.3	7.3
80-89	10.3	8.9	14.6	13.5
70-79	38.5	22.8	39.6	26.2
60-69	35.8	44.9	35.4	45.7
50-59	5.1	19.3	2.1	7.3
	100	100	100	100

of 60%–80%, and only in 6.7% was a marginal discrimination between brain states possible (see Table I for details).

The BCI system uses two types of experimental sessions: 1) training sessions where data are collected to set up a subject-specific classifier (with or without feedback) and 2) sessions where the classifier is used to classify a subject's EEG online while motor imagery is requested (with feedback). Table II divides the classification results into sessions without feedback (S1) and sessions with feedback (S2) for RLS and BP. An interesting result is that nonfeedback sessions have a higher accuracy than feedback sessions. S1 of RLS and BP have almost the same performance, but results for S2 differ. Feedback sessions with BP show better results.

VI. CONCLUSION

The results presented show that a large population can perform a BCI operation, and that a high accuracy of above 90% can be achieved. We know from other investigations that even subjects who have no BCI control in the first few sessions can learn the operation by neuro-/biofeedback training [6], [14], [15].

Feedback plays an essential role in BCI skill development as indicated by several investigations [6], [8], [11], [15]. Feedback can be expected to improve the classification accuracy simply by maintaining the subjects' interest and attention. However, feedback can also degrade performance due to insufficient attention to the imagination or frustration caused by incorrect feedback. Especially during their first attempts at BCI operation, subjects sometimes get overwhelmed by the new experience of controlling a technical device with their thoughts. It is possible that this explains why the nonfeedback sessions gave better results than the feedback sessions. However, the 99 subjects of this study established almost the same results for feedback and nonfeedback sessions, although it was a new experience for them and the experiments were performed in a field experiment at an exposition.

Splitting the results in RLS and BP algorithms shows that both yield to almost the same performance. BP results are slightly superior to RLS results, however. The reason is the robust design of the band-power estimation that suppresses the influence of artifacts. The advantage of using AAR parameters is that no subject-specific frequency range selection, which further improves the classification results [14], is necessary. However, the estimation of the AAR parameters is sensitive to artifacts. Hence, classification results can be biased, i.e., the horizontal feedback bar is more likely to extend in one direction than in the other direction. To overcome this problem, more training data must be used to set up the classifier.

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