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Voluntary brain regulation and communication with electrocorticogram signals

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ABSTRACT

Brain–computer interfaces (BCIs) can be used for communication in writing without muscular activity or for learning to control seizures by voluntary regulation of brain signals such as the electroencephalogram (EEG). Three of five patients with epilepsy were able to spell their names with electrocorticogram (ECoG) signals derived from motor-related areas within only one or two training sessions. Imagery of finger or tongue movements was classified with support-vector classification of autoregressive coefficients derived from the ECoG signals. After training of the classifier, binary classification responses were used to select letters from a computer-generated menu. Offline analysis showed increased theta activity in the unsuccessful patients, whereas the successful patients exhibited dominant sensorimotor rhythms that they could control. The high spatial resolution and increased signal-to-noise ratio in ECoG signals, combined with short training periods, may offer an alternative for communication in complete paralysis, locked-in syndrome, and motor restoration.

1. Introduction

During the last decade, there has been rapid progress in research on brain–computer interfaces (BCIs). The number of studies published increases almost exponentially. For acquisition of brain signals for BCI control, primarily different types of noninvasive recording systems, such as the electroencephalogram (EEG) [1–3], the magnetoencephalogram (MEG) [4], and functional magnetic resonance imaging (fMRI), have been used [5,6]. Learning to control epileptic seizures through voluntary regulation of EEG signals such as slow cortical potentials [7,8] and sensorimotor rhythms [9] also has a long tradition (for a review, see Birbaumer and Cohen [10]). Invasive techniques allowing for single-neuron recording using implanted microelectrodes were tested first in primates by Nicolelis [11] and Donoghue [12], and then in human tetraplegic patients by Hochberg et al. [13] and Donoghue et al. [14]. Recently, the electrocorticogram (ECoG) recorded with implanted subdural electrode grids was successfully applied to control of a BCI in presurgical patients with epilepsy [15–21].

Most noninvasive approaches to communication using the EEG suffer from a very slow communication speed of only about one to five letters per minute. Therefore, BCI applications have been developed mainly for patients with neurodegenerative diseases such as amyotrophic lateral sclerosis (ALS), a disease that can lead to a state of complete motor paralysis with intact sensory and cognitive functions. One of the most terrifying aspects of this “locked-in syndrome” is that the loss of muscle control prevents the expression of even the most basic needs. However, because perceptual and cognitive functions are usually unaffected, direct interaction between brain and computer may offer a unique communication channel for locked-in patients. This was the goal of a BCI named the *thought translation device* (TTD), which was developed to reestablish communication with severely paralyzed patients [1,22,23]. It was the first BCI that enabled several patients with ALS to communicate verbally using their slow cortical potentials only [1]. The limited signal-to-noise ratio in the EEG is one reason for the slow communication speed and the extremely long training periods in neurofeedback of epilepsy [24]. In an attempt to increase the signal-to-noise ratio for EEG algorithmically, spatial or spatiospectral filtering methods [25,26] or knowledge from previous BCI sessions [27] has been used. A more direct approach to improving the signal-to-noise ratio is the use of subdural electrodes that detect the ECoG signal directly from the cortex. ECoG signals have up to 10 times higher amplitudes with a broader frequency range (0 to approximately 300 Hz) from more

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focused locations than EEG signals. All these features lead to an increased signal-to-noise ratio and, therefore, potentially to an increased rate of information transfer in a BCI. Studies investigating ECoG discrimination of hand and tongue movements, carried out by Leuthardt et al. [21], support our approach to the use of those tasks. Here, we report on actual brain–computer communication via ECoG signals of imagined movements within very short training periods using a modern signal processing and classification approach.

2. Methods

2.1. Approach

In the predominant approach to realizing a BCI, oscillatory EEG components, such as motor-related mu rhythms or sensorimotor rhythms (SMRs), are used. During movement or imagination of a movement, the SMR decreases over the corresponding area, which is referred to as event-related desynchronization (ERD), and resynchronizes afterward, which is referred to as event-related synchronization (ERS). Pfurtscheller and Aranibar trained the regulation of the ERD/ERS [28]. In the 1990s, Pfurtscheller et al. developed BCIs based on detecting ERD and ERS of mu and beta rhythm bands during imagined left and right hand movements [3,29,30]. In parallel, Wolpaw's group developed a mu rhythm-controlled BCI [2,31]. Müller and co-workers introduced machine learning methods for application in SMR BCIs [32,33]. Another EEG component that can be voluntarily controlled is the slow cortical potential (SCP). SCPs are slow potential shifts located in the frequency range below 1 Hz. Birbaumer and colleagues first used self-regulation of SCPs with neurofeedback to reduce seizures in patients with drug-resistant epilepsy [7,34]. With the development of the TTD, voluntary control of SCPs has been used as an alternative form of communication for completely paralyzed patients [1,35]. In this study, the TTD was used for direct brain–computer communication with oscillations extracted from ECoG signals in patients with epilepsy.

Here, we emphasize three important issues for realization of an ECoG-driven BCI: (1) rapid training of the BCI system by use of an autoregressive feature extraction and an efficient support-vector machine classifier (SVM) with embedded feature selection for automatic channel selection (all methods have been implemented for online use in our BCI); (2) immediate introduction of a spelling application; (3) an offline analysis that delivers predictive information about the conditions for successful applications in the future.

2.2. Subjects and clinical environment

The BCI experiments were performed in the Department of Epileptology of the University of Bonn. All five patients aged between 21 and 46 years had focal epilepsy. To localize the epileptic focus prior to surgery, grids or strips of electrodes were placed under the dura, onto the surface of the cortex, to record the ECoG [36]. In some patients, additional electrodes were placed in deeper regions of the brain such as the hippocampus. The platin electrodes on the grids were arranged at a distance of 1 cm and had an electrode diameter of about 4 mm. All patients had 64 to 84 surface electrodes, which at least partly covered the primary motor and premotor area. Four patients had a 64-electrode grid arranged in an 8×8 matrix over the left or right motor cortex, and one patient had a 5×4 electrode grid covering the left central motor and premotor cortex, including the hand and foot area, plus four 16-electrode strips covering most of the frontal cortex without reaching the temporal cortex (see Table 1).

The ECoG was continuously recorded over a period of 5 to 14 days. BCI experiments could be carried out in only a short time frame of a few days between clinical examinations before the operation when the electrodes were removed again. Therefore, control of ECoG and communication with a BCI had to be achieved with very little training. Furthermore, the cognition and attention of most of the patients were restricted because of epilepsy, medication, and surgical stress. Most of them could not concentrate for longer periods, which limited our experiments to a short duration per session.

To record every epileptic seizure, the data had to be recorded continuously without interruption. Therefore, it was not possible to replace the standard ECoG recording and analysis software (Stellate) with the BCI for the experiments. Moreover, a program had to be developed interfacing the connection between the ECoG amplifier hardware and the Stellate recording software that branched off the data stream and sent it via socket connection to the BCI, which is a specially developed version of the TTD [37] (Fig. 1a). The ECoG signal was sampled at 1 kHz and recorded with a bandwidth of 0.016 to 300 Hz.

2.3. Experimental procedure

The subjects were seated in their bed or in an armchair facing a computer screen at a distance of 1–2 m. They were asked to repeatedly imagine one of two different movements. The experiment consisted of a BCI training phase and a communication phase. During the BCI training phase, ECoG data from a few hundred trials of the two tasks were collected. These data were then fed into the algorithms for autoregressive (AR) modeling, channel selection, and classification (see below and Fig. 1b and c). The resulting channel subset and the trained classifier were used in the second part of the experiment to classify the brain signals online. Here the classifier output of each trial was used as a control signal for a spelling application. To demonstrate the control of the BCI, the patients were asked to write their name using the two imagery tasks.

Motion imagery tasks were chosen for controlling the BCI because of the location of the grid near and over motor regions. "Imagining finger or hand movements" and "imagining tongue movement" were chosen as the two conditions to be discriminated. Both tasks are expected to exhibit well-localized signals in a relatively large area of the motor cortex. In a frequency analysis, the ERD/ERD of the mu rhythm should be a discrimination feature.

To match the situation of BCI use in completely paralyzed patients, actual movements were avoided. Therefore, patients were supervised with a video system to ensure that no actual movements were made. Recording of EMG for more precise control of muscular activity was not possible for technical reasons. It might be possible that some muscular activity did occur; however, there should have been no actual movement artifacts. Even by controlling motor response with the EMG, it is not possible to generalize to paralyzed patients because of the high interindividual variability of remaining motor functions.

At the bottom of Fig. 1b a screenshot of the projection screen is shown in which a subject wrote the word *ANGELO*. The lower left box contained the spelled letters *ANGEL*. On each trial the subject imagined a movement to navigate within a binary spelling tree. In the present situation, in Fig. 1, the next letter 'O' to write is not contained in the letters in the right box. Therefore, the subject had to reject this subset of the alphabet by imagining finger movements indicated by the thumbnail picture added underneath as a reminder. The subject had to wait for a letter set that contained the 'O' and then select it by imagining a tongue movement. After each selection the selected letter set was split into two halves, which were subsequently presented during the following trials for either selection or rejection. This process continued until a single letter was presented that could be selected and thereby added to the spelled text in the left box. A letter set consisting of 32 letters used here would require five levels leading to selection of a letter, with a minimum of 5 to 10 trials including options for corrections. For a detailed description of the spelling paradigm, see Perelmouter et al. [38].

2.4. BCI training paradigm

Depending on the patients' availability, 100 to 378 trials of imagery were collected for training of the classifier. After each run of 50 trials, the patient was offered a short break. During the first second of each trial, a fixation cross was

Table 1
Overview of the training procedure, classification, and BCI outcome for five patients

	Gender/ age/ handedness	Location of grid electrodes	Classifier training		Online test of classification		Copy spelling		
			% Correct	No. of trials	% Correct	No. of trials	% Correct	No. of trials	Text written
Patient 1	M/21/right	64 right							
Session 1			*74*^{b}	210	94^{b}	128	–	–	–
Session 2			*87*^{b}	150	80^{b}	98	64	157	ANGELO
Patient 2	F/22/right	20 left central + 4 × 16 frontal	*63*^{b}	100	87^{b}	27	73	244	MOMO
Patient 3	F/41/right	64 right	*62*^{b}	200	–	–	–	–	–
Patient 4	F/34/right	64 left	*74*^{b}	200	–	–	77	164	SUSANNE
							88	73	*surname*
Patient 5	M/46/left	64 left	*69*^{b}	150	72^{a}	50	64	350	–

Note. The percentage of correct responses was defined as the number of correctly classified finger and tongue movements imagined divided by the total number of trials. The performance of the classifier training runs was the cross-validation result of the SVM classifier on the data of the training procedure (offline result in italics). For the training and online test data, a one-tailed binomial test was used to calculate the probability of a nonchance result indicated by $^{a}P < 0.01$ and $^{b}P < 0.001$.

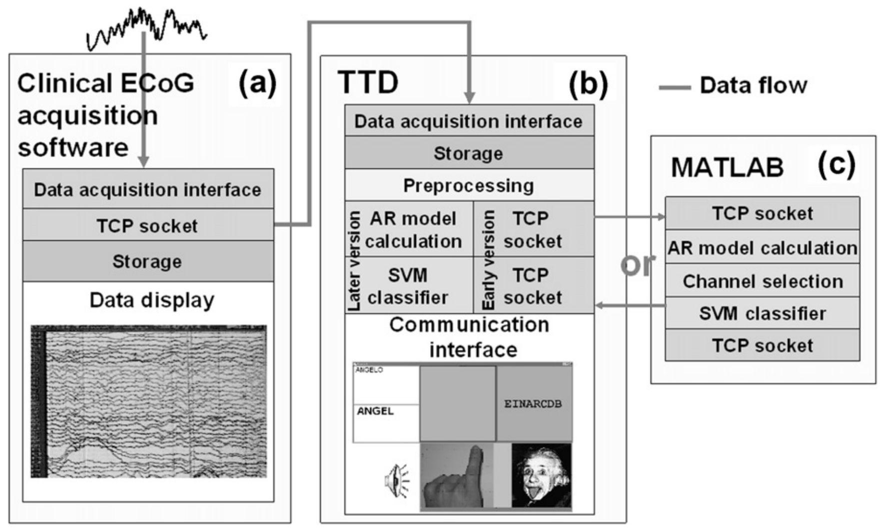

Fig. 1. Modules of the ECoG-driven BCI: (a) ECoG data acquisition software records the signals continuously. A socket connection was programmed to branch off the signal to feed the TTD. (b) After preprocessing, the data from each trial were subject to calculation of AR coefficients, which were then classified by a SVM. The classification results were used to operate the communication interface for letter selection. (c) In an early stage of the experiments, calculation of the AR coefficients as well as the SVM classifier was not implemented in the TTD. A TCP/IP socket connection between the TTD and the Matlab application allowed for real-time data exchange and online classification using Matlab. After successful tests, the algorithms were inserted into the TTD without Matlab.

displayed in the center of the screen. The following 4-second imagination phase started with a cue that was presented in the form of a picture showing either Einstein's tongue or a hand with an outstretched little finger. The task sequences were balanced in pseudo-randomized order. The trial ended with 2 seconds of rest. The structure is illustrated in Fig. 2.

A BCI session was subdivided into four steps: (1) a training phase in which the patient was asked to imagine the tasks in a sequence predefined by the computer without receiving feedback; (2) training of a classifier using the ECoG data of the training phase while the patient could take a break and rest; (3) an online classification test run in which the patient received feedback about the classification result after each trial (after each correctly classified trial, a smiley face was presented for 1 second); (4) a copy spelling phase in which the patient was asked to spell his or her name by following the aforementioned spelling procedure. The computer assisted the patient in getting used to the letter selection procedure by highlighting the target necessary for a correct selection or rejection response.

2.5. Data processing

The basic procedure in signal processing of a BCI comprises two steps. First, a feature selection algorithm is applied to the acquired data (i.e., the ECoG) to reduce the highly dimensional multichannel sampled data stream into a few meaningful feature values only. In the present study this was done using an AR model and a channel selection algorithm (see below). Second, those feature values are fed into a classification algorithm that learns how to discriminate ECoG signals of the two imagery classes (here, either finger or tongue movement imagination). Once the classifier has been trained in an offline procedure, it can be used to discriminate feature values from new, unseen signals in an online application. The SVM is a classification algorithm that has been proven to perform very well on a large range of problems. In the standard formulation, the SVM is able to deal with overlapping class distributions. For our results, we used a linear SVM. For its training, the feature values of 100 or more trials were used. The feature values of one trial were taken from data from selected electrodes in a window of 3.5 seconds' duration, starting half a second after visualization of the task cue, as displayed in Fig. 2. Thus, for each trial and electrode, an ECoG sequence consisting of 3500 samples was obtained. The linear trend from every sequence was removed.

For feature selection, an AR model was fitted to each sequence according to Lal et al. [39], Haykin [40], and Pfurtscheller et al. [3]. A model order of $M = 3$ was found to give the lowest offline cross-validation error. The concatenated model parameters ($M = 3$ per channel) of all k ECoG channels, together with the descriptor of the imagined task (i.e., $y = +1$ for finger and $y = -1$ for tongue imagination) form one training point. A training point ($\boldsymbol{x}; y$) is therefore a point in $R^{Mk} \times \{-1, 1\}$. The model vector $\boldsymbol{x}$ consisted of 3×64 coefficients when recording from a 64-electrode grid.

Each training point was then classified by a SVM classifier. The SVM is a classification technique developed by Vapnik [41] and colleagues (see [42,43]) which has been demonstrated to perform well in a number of real-world problems, including the BCI e.g., [39,44]. The central idea is to separate the n training trials $\boldsymbol{x}^{(i)} \in \mathrm{R}^d$ ($i = 1\ldots n$) into two classes by finding a weight vector $\mathbf{w} \in R^d$ and an offset $b \in R$ of a hyperplane in the $d = Mk$ dimensional parameter space,

$$H : R^d \to \{-1, 1\}; \quad \mathbf{x} \to \mathrm{sign}(\mathbf{w} \cdot \mathbf{x} + b),$$

with the largest possible *margin* (i.e., distance between the hyperplane and the nearest training point). The SVM has been shown to provide theoretical advantages in terms of generalization ability [41].

For this analysis, we used a linear SVM as described by Lal et al. [39]. Via 20-fold cross-validation within the training set, we estimated the *regularization* parameter of the SVM (the trade-off between the exact fit to the data and the simplicity of the

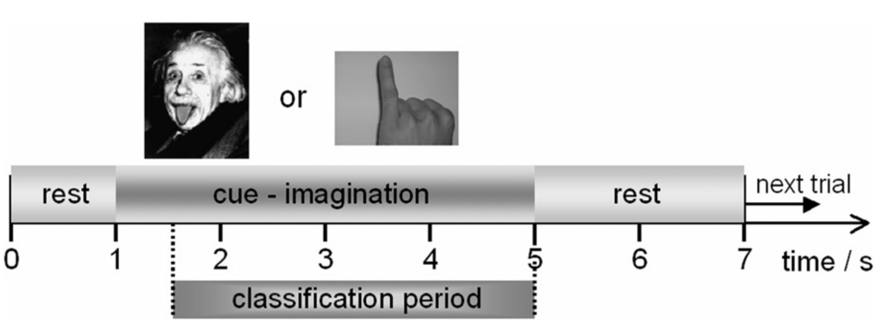

Fig. 2. Trial structure during the data collection phase. Each trial started with a 1-second resting period. During the following 4-second imagination phase, a picture of Einstein's tongue or a hand was shown as a cue to imagine hand or tongue movement. The period used for classification started 0.5 second after the cue onset. Each trial ended with a 2-second resting period.

fitted model—see Schölkopf and Smola [43]) as well as the optimal subset of channels (see below). We then trained a single SVM on the training data using these estimated *hyperparameters*, and this SVM was applied to the test data, that is, the signals subsequently recorded for classification during the online test phase and the online copy spelling phase. For offline evaluation of the classification performance of the system, we used a double cross-validation scheme: 20 times, the available data were split randomly into a training set (90%) and a test set (10%) and the aforementioned procedure was carried out—cross-validation for hyperparameter selection is therefore carried out multiple times, once within each training subset.

2.5.1. Reduction to relevant channels

Automated selection of relevant recording channels can increase the classification performance of a BCI system [45], but the problem of how to rate the relevance of a recording channel in the presence of possible nonlinear interactions between channels is not trivial. As the number of training trials is small compared with the number of channels and as the signals are noisy, the overall accuracy is not necessarily monotonic in the number of channels used. Some feature selection methods try to overcome this problem by optimizing the feature selection for subgroups of fixed sizes (e.g., plus-l-take-away-*r* search) or by implementing floating strategies (e.g., floating forward search). For an application of ECoG channel selection that delivers a spatial interpretation of the selection results, it is necessary to treat some features homogenously: numerical values belonging to one and the same channel have to be dealt with in a congeneric way. Generic algorithms, for example, can choose subgroups of arbitrary size during the feature selection process. They have successfully been used for the offline selection of EEG channels [46,47] in BCI applications, but proved too slow for online use during an experiment. For this reason, we adapted the SVM-based feature selection method recursive feature elimination (RFE) to implement these specific requirements. The use of this method could reduce the number of relevant ECoG channels to about 10% of the original channels without loss in classification accuracy and even with increased performance.

2.5.2. The correct response rate as performance measure

During the experiment the correct response rate was defined as the percentage of correctly classified trials in a run or session. Runs from the initial training phase were classified directly afterward using the SVM cross-validation procedure. In the binary task paradigm, 50% correct responses would be expected by chance. For the online test and copy spelling phases, the correct response rate was directly available. In Table 1 the correct response rates of all trials in each phase are reported. However, for successful navigation through the letter selection tree in copy spelling, the ratio of correctly classified finger and tongue imaginations (selections and rejections) is relevant dependent on the number of letters or words to spell. Therefore, for the spelling task, the correct response rate provides a rough estimate of performance only, whereas for the training and online runs, the significance of results can be estimated with a significance test. Therefore, additional significance measures—one-tailed binomial tests—are reported for the training and online tests only.

2.6. Offline analysis

Although the three coefficients of the AR model reflect the amplitude of the predominant oscillatory activity of the signal, they do not tell us directly the frequencies that were most useful for classification. Closer inspection of the data sets was therefore necessary to identify the physiological responses driving the system. In an offline analysis, a fast Fourier transform (FFT) was applied to each channel, each condition (tongue or finger), and several time windows during a trial. The color map in Fig. 4 represents the squared correlation r^2 between target and spectral amplitude at a certain frequency, electrode, and time window. The r^2 value is a rough measure of the separability of the features of the two conditions under the assumption of a normal distribution. For analysis of the time course of ECoG response, a trial was subdivided into six time frames each 2 seconds wide. Each frame was windowed by a Hamming window before calculation of the FFT which therefore reflected predominantly the 1 second in the middle of the window. The first window started 1 second before cue onset. For calculation of r^2, the FFTs of all trials were averaged separately for each task condition, time, and frequency.

3. Results

3.1. Subjects and online results

Five subjects (two male, three female) with an implanted electrode grid over the brain region covering the hand and/or tongue area participated in BCI training. The procedure was approved by the ethics committee of the Faculty of Medicine of the University of Tübingen. For patients 1 and 4, the location of the hand or tongue was verified with electrical stimulation, which was carried out during grid implantation. All patients were instructed to imagine either tongue movement or movement of the fingers of the contralateral hand without actually moving the tongue or any finger.

Patient 1 participated in two sessions, whereas patients 2 to 5 attended one session only. The percentage of correct responses defined by the number of correctly classified imagined finger and tongue movements, divided by the total number of trials, served as the performance measure. Patient 1 could reach a performance level of 94% correct responses during the online test period, which was far better than the 74% classification result of the training runs. Unfortunately, he was too tired and exhausted to continue with the spelling task that day. After starting the second session the day after with three training runs classified with 87%, he achieved 80% correct responses in the test runs, whereas his performance was only 64% in the spelling condition. However, he managed to spell his name *Angelo* in 157 trials requiring 18:19 min. With 100% accuracy, he could have written his name within 39 trials, as one letter can be selected in 5 to 10 trials which would have taken 4:33 min or 1.32 letters/minute. Patient 2 had 4×16 frontal electrodes and only a smaller grid with 20 electrodes left centrally, which probably did not cover the hand area very well. After 100 trials of poor classification performance in training, we tried an online test in which she performed excellently (87%). This encouraged us to proceed to the spelling immediately. With this very short period of practice, she achieved an overall copy spelling performance of 73% and needed 28:28 minutes to spell her four-letter nickname. Patient 3 did not improve after 200 runs of training, and therefore, we did not continue with further testing. Comparable to our BCI training with locked-in patients, an accuracy of 70% was defined as prerequisite to introduction of a spelling application [38]. Patient 4 was directly confronted with the copy spelling task after 200 trials of training with an average accuracy of 74%. She managed to spell her seven-letter first name in 164 trials (19:08 minutes) and her seven-letter surname in only another 73 trials (8:31 minutes or 0.82 letter/minutes). This increase in performance suggests a very rapid learning process. Although the communication rates do not exceed those of some excellent EEG-driven BCIs in healthy people, a comparable result within the first session was never reached by patients to our knowledge [14,48]. Patient 5 with a very low IQ of 58 was confused by the procedure. He was not able to spell his first name despite a basic performance level of 72% during the online classification test. Table 1 provides an overview of the patients and their performance.

3.2. Offline analysis

Fig. 3 illustrates a representative r^2 time course during the classification test runs for patient 1, showing a peak activation about 2 seconds after target presentation that slowly decayed to the end of trial. The most discriminative frequency was 11 Hz. A second peak at around 20 Hz, the so-called beta peak, is sometimes also present in healthy subjects [49]. The most significant activations were found between 1 and 3 seconds in all participants. Sometimes, this was delayed by 1 second in the final copy spelling task, which could easily be explained by the cognitive load of the novel and complex spelling task.

The maps in Fig. 4 illustrate the discriminative effect size between the imagery tasks for all patients. The color coding reflects the effect size defined by the difference between tasks referred to the pooled SD. Subtraction of the amplitude in the finger movement imagination task from that of the tongue movement imagination task led to a positive effect size depicted in red for ERD over the hand area; blue reflects either an ERD during the tongue movement imagery task or an ERS during finger movement imagery. The larger spectral maps within a frequency range of 0 to 70 Hz are shown for those three patients who could spell their

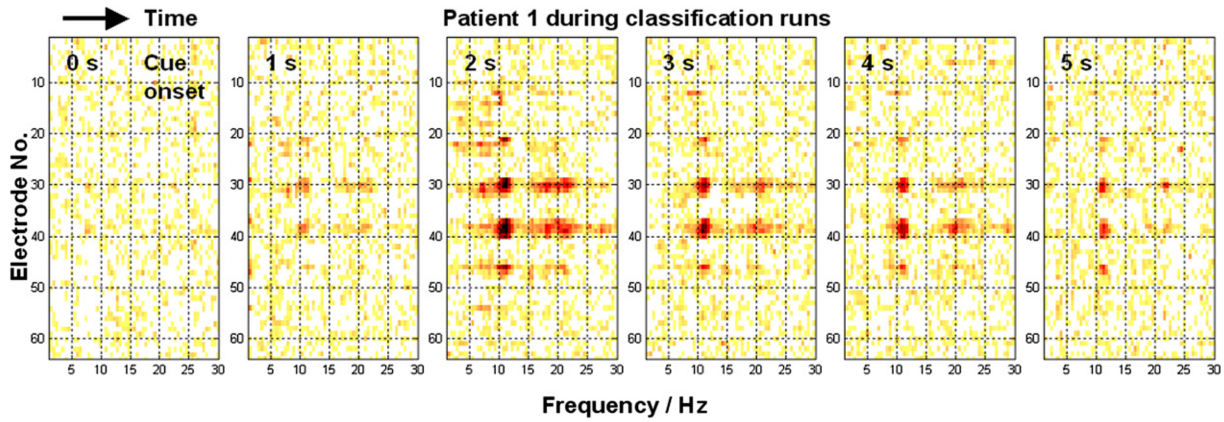

Fig. 3. Discriminative power in the frequency range 0 to 30 Hz for all electrodes and for six time windows during a trial. One hundred fifty trials were averaged.

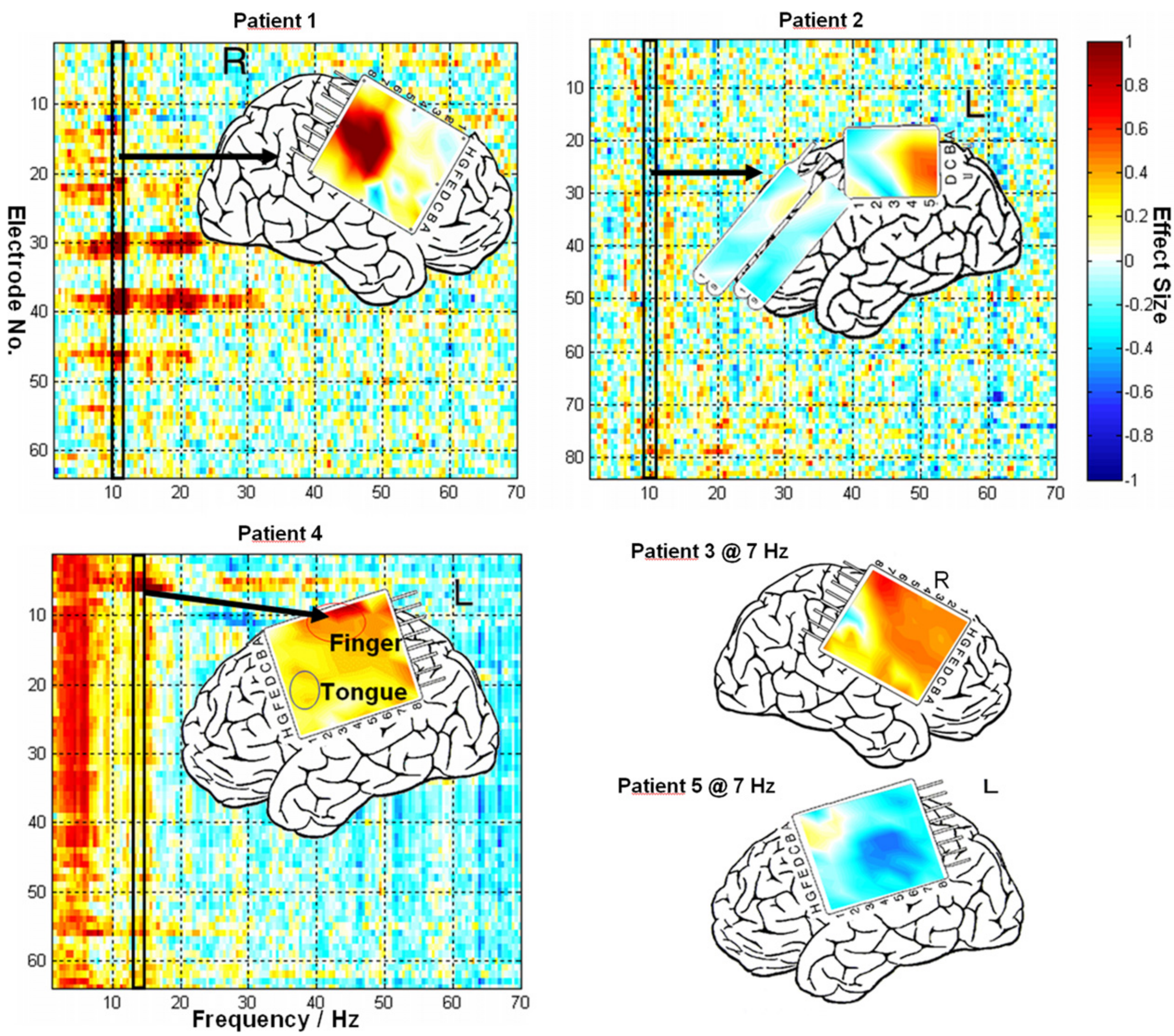

Fig. 4. For the three patients who successfully spelled their names, these detailed spectral activation maps illustrate the frequency range from 0 to 70 Hz for all electrodes. For all five patients, grid mapping indicates the location of the grids and the differentiation in the most predominant frequency band. Red indicates an ERD during finger movement imagery, and blue, an ERD during tongue movement imagery.

names successfully. At some electrodes, the first two patients showed high effect sizes in the mu rhythm band (around 10–11 Hz). Patient 4 also showed a highly specific local 15-Hz peak at the area of the finger, which was verified by electrostimulation. Additionally, she could control the broadband activity below 8 Hz that was of unknown origin. Patients 3 and 5, who did not succeed in spelling their names, had their largest effect sizes around 7 Hz (also at 23 Hz in the case of patient 5).

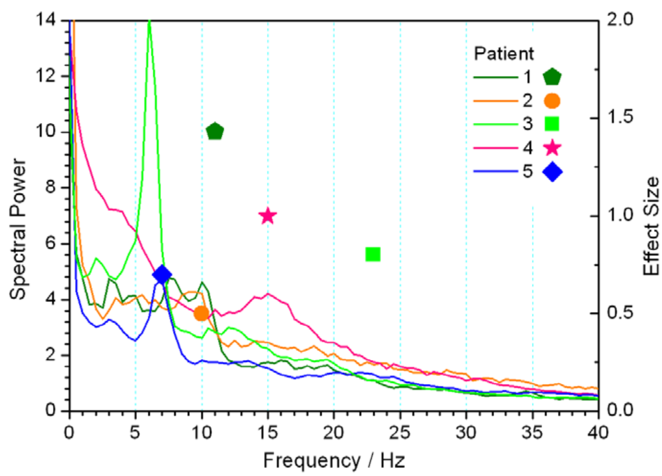

Fig. 5. Spectral power density at the best classifiable electrode for all patients. The dots indicate the effect size at the best classifiable frequency, which ideally should match the SMR frequency. The successful patients (1, 2, and 4) have both the best effect size and peak frequency in the range 8 to 15 Hz, whereas for the unsuccessful patients, theta waves were predominant.

The three AR coefficients reflect the most dominant one to two frequencies. Therefore, for optimal classification, those frequencies should also be the most discriminative. This is the case for subjects showing SMRs over sensorimotor areas. To prove this assumption in patients with epilepsy who might have a more or less compromised sensorimotor area, Fig. 5 shows the power spectrum over the best classifiable electrode for each patient. Although for those patients who successfully spelled their names, frequency peaked in the range 8 to 15 Hz, for the unsuccessful patients, there was a strong peak in the upper theta band at 6 to 7 Hz. For patient 5, the strong theta activity was not reliably classifiable. Instead, he showed 23-Hz activity that could be classified in the training session but vanished during the spelling task.

4. Discussion

In three of five patients with epilepsy in whom electrode grids were implanted over the motor area, we tested the hypothesis that with the increased signal-to-noise ratio of ECoG and the use of an advanced feature selection and classification algorithm, voluntary control of ECoG oscillations and spelling of letters are possible within the first few training sessions. The results suggest that in BCI training using subdurally implanted electrodes in combination with the SVM classification of AR coefficients, rapid training success is possible, even though the training procedures reported previously (mostly in patients with ALS) using surface EEGs [7,9,34] required extremely long periods, up to 100 sessions.

The question arises why patient 1 could easily spell his name with a performance rate of only 64%, while patient 5 could not despite having the same total correct response rate. In fact, patient 1 achieved 89% correct selections with only 48% correct rejections. This means that with a correct rejection rate of 50% (chance), one is able to spell if selection responses are reliable and large enough. Patient 5 also reached 89% correct selections but he succeeded in only 20% of his rejections. Depending on the letters to select and the erroneous paths he had to follow in the letter selection tree, the performance of patient 5 was not sufficient. The low IQ of this patient might have contributed to these problems. The power spectrum of the unsuccessful patients uncovered a clear indication for reduced awareness by showing a strong 6- to 7-Hz peak frequency. One should also note that the most successful patient, No. 4, was the only one who had the grid over the motor cortex contralateral to the dominant hand. Imagining movement of the dominant right hand should lead to better classification results in the contralateral left motor cortex. Additionally, the left hemispheric grid is supposed to support classification accuracy of tongue movements because speech-related areas are located in the left hemisphere close to the motor cortex.

A major problem in training people in one session with a BCI becomes obvious when comparing the activation patterns of the three training stages, particularly online classification and copy spelling. Most of the subjects showed large variations between runs and sessions. One reason might be that they have not automated their task sufficiently. As they receive feedback in the last two stages only, they might also be distracted by incorrect classification results. A third reason is the complexity of the copy spelling task. Despite the fact that patient 4 managed to spell her first name and surname quite rapidly, the correct activation pattern was delayed in the spelling task by about 1 second compared with the training condition. An improvement in classification could be achieved by adapting the classification period to each individual's online spelling response curve instead of using the whole feedback interval.

Final clarification of the superiority of ECoG over EEG can be achieved only by simultaneous measurement. The impairment in patients with epilepsy resulting from postsurgical pain, problems with cognition caused by seizures, and the placement of electrode grids always at the epileptic focus gives rise to the assumption that better training results can be achieved. Comparison of performance with the results of BCI training with students in the MEG, as carried out by Lal et al. [39], in which 4 of 10 subjects could spell their names with the same system after one session, suggests that the ECoG should be superior to the MEG considering that all patients with "normal" spectral distribution were able to spell their names within one or two sessions.

In this study, the presence of normal sensorimotor rhythm activity seemed to be a strong predictor of ability to learn brain–computer control and communication. This also supports the hypothesis that normal mu or sensorimotor rhythms are necessary to operate a BCI with ECoG from the motor cortex. In further investigations of BCIs using ECoG signals, simultaneous measurement of the EEG will be important. Here, we have presented a BCI device that, within one or two training sessions, enabled three of five patients with epilepsy to regulate their sensorimotor rhythms and use them for communication.

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