Real-Time EEG Analysis with Subject-Specific Spatial Patterns for a Brain–Computer Interface (BCI)

C. Guger, H. Ramoser, and G. Pfurtscheller

***Abstract*—Electroencephalogram (EEG) recordings during right and left motor imagery allow one to establish a new communication channel for, e.g., patients with amyotrophic lateral sclerosis. Such an EEG-based brain–computer interface (BCI) can be used to develop a simple binary response for the control of a device. Three subjects participated in a series of on-line sessions to test if it is possible to use common spatial patterns to analyze EEG in real time in order to give feedback to the subjects. Furthermore, the classification accuracy that can be achieved after only three days of training was investigated. The patterns are estimated from a set of multichannel EEG data by the method of common spatial patterns and reflect the specific activation of cortical areas. By construction, common spatial patterns weight each electrode according to its importance to the discrimination task and suppress noise in individual channels by using correlations between neighboring electrodes. Experiments with three subjects resulted in an error rate of 2, 6 and 14% during on-line discrimination of left- and right-hand motor imagery after three days of training and make common spatial patterns a promising method for an EEG-based brain–computer interface.**

***Index Terms*—Brain–computer interface (BCI), common spatial patterns (CSP), event-related desynchronization (ERD), real-time software.**

I. Introduction

OSCILLATORY electroencephalogram (EEG) components have been used as an input signal for a brain–computer interface (BCI) [1]–[3]. Patients in a late stage of amyotrophic lateral sclerosis (ALS), for example, can communicate with their environment with such a system using a simple binary output signal to select letters, symbols, or words on a computer monitor [3] or to control a robotic device [4], [5].

In order to achieve appropriate human–computer interaction in these systems, it is necessary to extract reliable parameters from the EEG. Rhythmic EEG components (such as mu and beta rhythms) were used since sensorimotor rhythms display an event-related desynchronization (ERD) close to contralateral primary motor areas during hand movement imagination [6]. This focal amplitude attenuation of contralateral mu and beta components is also accompanied by enhancement [event-related synchronization (ERS)] [7] of similar frequency components on the ipsilateral hemisphere. To properly record these focal changes, the EEG electrodes have to be located close to the primary sensorimotor areas. It has been reported that by utilizing two bipolar electrodes close to C3 and C4, a single EEG trial classification accuracy of 80–95% can be achieved after approximately six to ten sessions [8]–[10]. However, since two bipolar derivations are insufficient to describe the overall brain activity, it seems reasonable to assume that more EEG signals recorded over sensorimotor areas, which are sensitive to differences between left and right imagery, would improve the classification accuracy of the BCI. Furthermore, although electrodes close to primary sensorimotor areas contain the most relevant information for discrimination [11], surrounding electrodes over premotor and supplementary motor areas also contribute some information to discriminate between brain states related to the motor imagery task.

The method of common spatial patterns (CSP) was first used in EEG analysis to extract abnormal components from the clinical EEG [12]. Recently, optimal spatial filters were devised for 56 EEG channels that lead to signals with optimal discriminatory power between two conditions [13]. This method weights each electrode according to its importance for the discrimination task and suppresses noise in individual channels by using correlations between neighboring electrodes. The classification rates for discriminating executed movements of the left and right index finger for three subjects were 84, 90, and 94%. Using the same method for data from a movement imagination task, an accuracy of 90.8, 92.7, and 99.7% was achieved for three other subjects in off-line analysis [14]. It was shown that the reference method (common average reference (CAR), bipolar, large Laplacian, small Laplacian, and referenced to the ear [15]) had minor influence on the classification accuracy [14]. Fast and continuous feedback can also enhance the performance of the system [8], [16].

The purpose of this paper is:

1) to test if it is possible to use CSP to analyze the EEG in real time in order to give feedback to the subject;
2) to determine the classification accuracy that can be achieved after only three days of training when the CSP filter is adapted between sessions.

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II. EEG Recording and Experimental Paradigm

Three subjects (17–26 years old, male) participated in this study. All were right-handed and free of medication and central nervous abnormality. All had previously served in a BCI study and were experienced in the experimental task. Subjects were paid per session.

Twenty-seven EEG electrodes (used to overlay the whole primary sensorimotor cortex), equally spaced with approximately 2.5 cm distance, were placed as shown in Fig. 1 and referenced to the right ear. A referential recording was selected because a classification accuracy similar to other referencing methods can be achieved (CAR, bipolar, large Laplacian and small Laplacian) [14] and does not require additional processing time for rereferencing. The ground electrode was located on the forehead.

An electrooculogram (EOG) was derived from an electrode placed medially above the right eye and a second electrode laterally below the right eye to detect vertical and horizontal eye movements. Averaging the data over trials and calculation of the spectrum showed that none of the subjects showed electromyogram (EMG) or EOG activity that could act as a control signal for the BCI.

The amplified EEG was bandpass filtered between 0.5 and 50 Hz and sampled at 128 Hz. The resolution was 12 bits. A notch filter was used to suppress the 50-Hz power line interference. An experimental procedure consisted of sessions with feedback, as shown in Fig. 2, and of sessions without feedback. The timing of the nonfeedback sessions was the same as that of the feedback sessions (see Fig. 2), except that the bar was not shown on the monitor.

Each session was divided into four or five (only for g3 and i2 in session 1) experimental runs of 40 trials, with randomized directions of the cues (20 left and 20 right) and lasted about 1 h (including electrode application, breaks between runs, and experimental preparation). Subjects g3 and g7 performed six sessions and subject i2 seven sessions.

III. Data Preprocessing

A. Artifact Detection

For the setup of the common spatial patterns, all trials were visually checked for artifacts in the time period 3–8 s (see Fig. 2). Trials that contained artifacts (EMG or range overflow of analog-to-digital converter) were discarded, because the CSP method is very sensitive to artifacts. A single trial containing, for example, a movement artifact can cause severe changes in the CSP [13]. The reason is the sample covariance (nonrobust estimate), which is used to estimate the covariance for the calculation of the spatial filters. During on-line operation of the BCI, the spatial filters perform a weighted spatial averaging of the EEG, and this reduces the influence of artifacts.

B. Temporal Filtering

All EEG channels were filtered (FIR filter) between 8–30 Hz, because this broad frequency range contains all mu and beta frequency components of the EEG, which are important for the discrimination task [2]. Müller–Gerking [13] showed that classification accuracy of left-hand movement, right-hand movement, and foot movement can be increased by using this broad range in comparison to narrow bands [alpha (8–12 Hz), lower alpha (8–10 Hz), upper alpha (10–12 Hz), beta (19–26 Hz), and theta (38–42 Hz)].

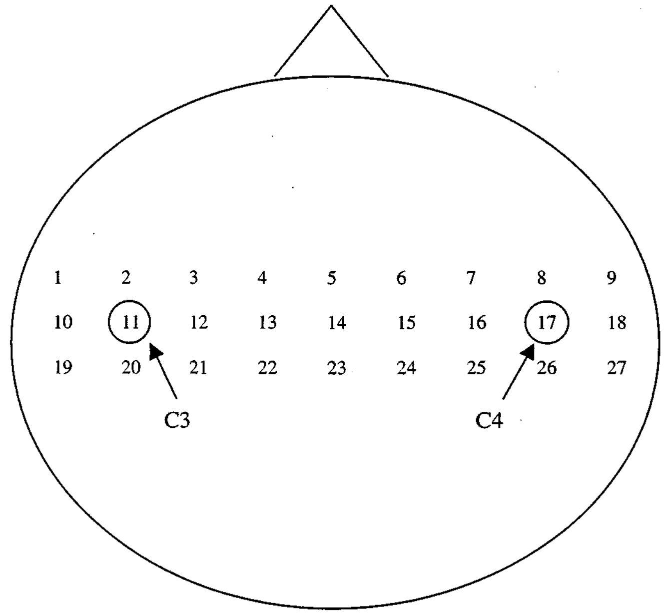

Fig. 1. Electrode positions. The 27 Ag/AgCl electrodes overlie the sensorimotor areas, which are activated during right- and left-hand movement imagination. Electrodes 11 and 17 correspond to C3 and C4 of the international electrode system.

IV. Common Spatial Patterns

The method presented here uses the covariance to design common spatial patterns and is based on the simultaneous diagonalization of two covariance matrices [17]. The decomposition (or filtering) of the EEG leads to new time series, which are optimal for the discrimination of two populations. The patterns are designed such that the signal that results from the EEG filtering with the CSP has maximum variance for left trials and minimum variance for right trials and vice versa. In this way, the difference between left and right populations is maximized, and the only information contained in these patterns is where the variance of the EEG varies most when comparing two conditions.

Given N channels of EEG for each left and right trial X, the CSP method gives an $N \times N$ projection matrix W according to [12]–[14]. This matrix is a set of N subject-specific spatial patterns, which reflect the specific activation of cortical areas during hand movement imagination. With the projection matrix W, the decomposition of a trial X is described by

$$\mathbf{Z} = \mathbf{W}\mathbf{X}. \tag{1}$$

This transformation projects the variance of $\mathbf{X}$ onto the rows of $\mathbf{Z}$ and results in N new time series. The columns of $\mathbf{W}^{-1}$ are a set of CSPs and can be considered as time-invariant EEG source distributions. After interpolation, the patterns can be displayed as topographical maps.

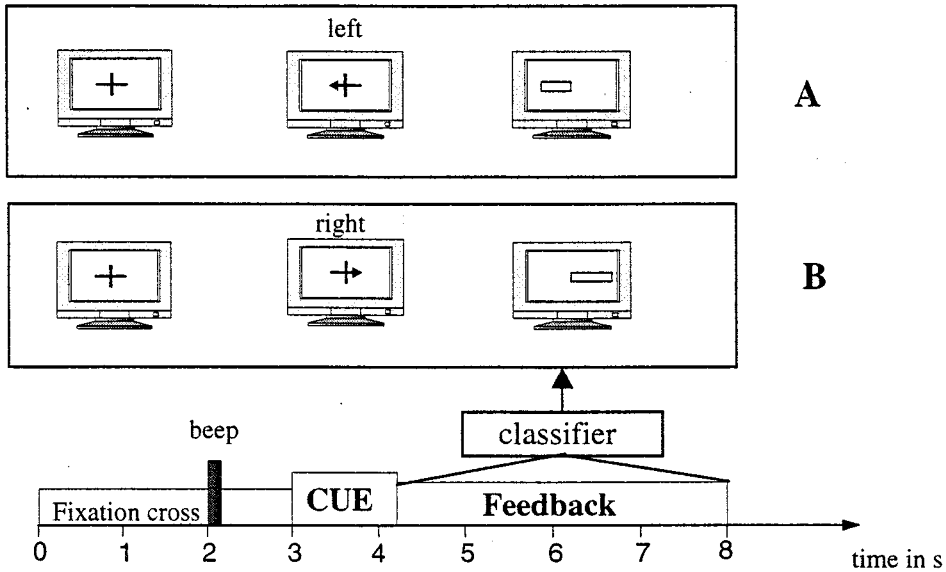

Fig. 2. Timing of one trial of the experiment with feedback. The subject sat in a comfortable armchair 150 cm in front of a computer monitor and was instructed to not move, to keep both arms and hands relaxed, and to maintain throughout the experiment the fixation at the center of the monitor. The experiment started with the display of a fixation cross that was shown in the center of a monitor. After 2 s a warning stimulus was given in form of a "beep." From second 3 to 4.25, an arrow (cue stimulus) pointing to the left or right was shown on the monitor. The subject was instructed to imagine a left- or right-hand movement, depending on the direction of the arrow. Between second 4.25 and 8, the EEG was classified on-line and the classification result was translated into a feedback stimulus in form of a horizontal bar that appeared in the center of the monitor. If the person imagined a left movement, then the bar, varying in length, extended to the left as shown in A and vice versa in B (correct classification assumed). The subject's task was to extend the bar toward the left or right boundary of the monitor, indicated by the arrow cue. 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.

By construction, the variance for a left movement imagination is largest in the first row of $\mathbf{Z}$ and decreases with the increasing number of the subsequent rows. The opposite is the case for a trial with right motor imagery.

For classification of the left and right trials, the variances have to be extracted as reliable features of the newly designed N time series. But it is not necessary to calculate the variances of all N time series. The method provides a dimensionality reduction of the EEG. A high number of EEG channels (N) can be reduced to only a few time series and a few spatial patterns. Müller-Gerking investigated the number of projections (2, 4, 6, 8, ...) to common spatial patterns used to build the feature vector [13] and showed that the optimal number of common spatial patterns used to build the feature vector is four.

After building $\mathbf{W}$ from an artifact corrected training set, only the first and last two rows $(p = 4)$ of $\mathbf{W}$ were used. The EEG data $\mathbf{X}$ were filtered with these p spatial filters. Then the variance of the resulting four time series is calculated for a time window T

$$\mathrm{VAR}_p = \sum_{t=1}^{T} \left(Z_{p(t)}\right)^2. \tag{2}$$

After normalizing and log-transforming, four feature vectors are obtained

$$f_p = \log\left(\frac{\mathrm{VAR}_p}{\sum_{p=1}^{4} \mathrm{VAR}_p}\right). \tag{3}$$

The log-transformation is performed to normalize the distribution of the elements in f_p. These features f_p are used to construct

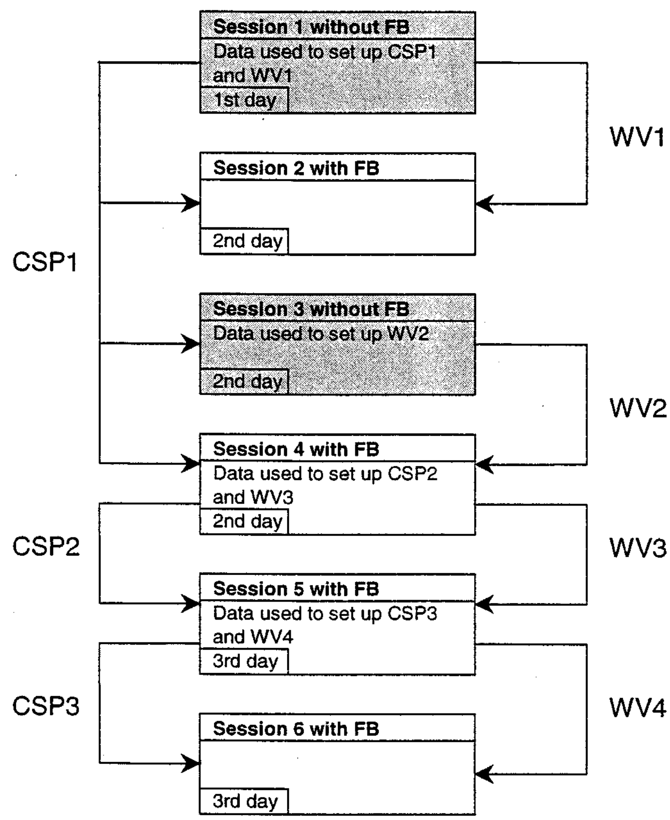

Fig. 3. Flowchart of six BCI sessions with and without (gray boxes) feedback (FB) for subject g3. Altogether, three CSP's and four WV's were set up. The sessions were performed within three days. Subject i2 participated in one session more after session 4, but the update procedure of the CSP's and WV's was similar to the one shown on this flowchart.

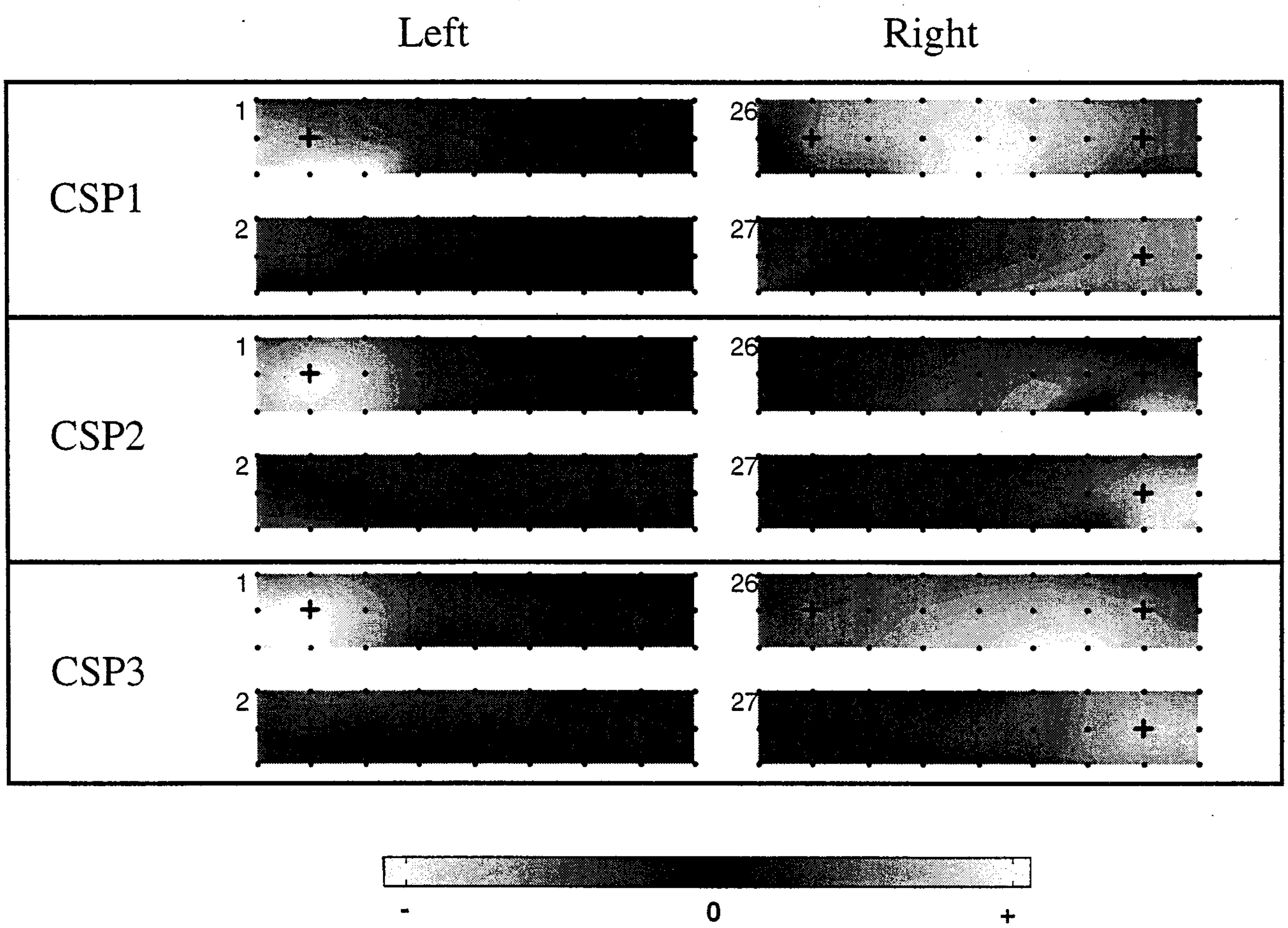

Fig. 4. Maps of the three calculated sets of common spatial patterns for subject g3 of session 1 (CSP1), 4 (CSP2), and 5 (CSP3). The small black dots indicate the 27 electrode positions. C3 and C4 are marked by the cross. The CSPs with index 1 and 27 are the most and 2 and 26 are the second most discriminating filters. Electrodes surrounded by black areas are of lower importance to the dicrimination task than electrodes surrounded by lighter colors.

a linear classifier [18], [19], referred to as a weight vector (WV) in this paper.

V. Data Analysis and Classification

Fig. 3 shows an exemplary (subject g3) experimental procedure. In session 1, feedback is not provided. Next, based on the 27-channel EEG recording from the first session, the first CSP (CSP1) was established with artifact-corrected data according to Table I.

TABLE I
AMOUNT OF TRIALS FOR THE SETUP OF THE CSPs OVER SUBJECTS AFTER ARTIFACT CORRECTION. SESSION 1 OF g3 AND i2 ORIGINALLY CONSISTED OF 200 TRIALS, ALL OTHER SESSIONS OF 160 TRIALS

Subject	CSP 1	CSP 2	CSP 3
g3	176	148	137
g7	150	125	122
i2	173	100	141

All error rates presented in this paper were calculated from the entire data set (160 or 200 trials) of one session. Thus, the error is not biased by individual artifact detection.

The CSP for all three subjects was calculated for specific time segments distributed over the interval from second 3 to 8. For each direction, only the two most important filters were used to calculate the features as described in (3). The classification accuracy was calculated with a 10×10 fold cross-validation procedure of a linear discriminant for each time segment in order to find the window length best suited for classification. The 10×10 fold cross-validation mixes the data set randomly and divides it into ten equally sized disjunct partitions. Each partition is then used once for testing; the other partitions are used for training. This results in ten different error rates, which are averaged. This is the error of a ten-fold cross-validation. To further improve the estimate, the procedure is repeated $10\times$ and again all error rates are averaged.

It was found that a higher accuracy can be achieved by increasing the window length, but this decreases the response time. The choice for all three subjects was setting the window length to 1 s, which has an accuracy in the range of a window length of 1.5 or 2 s and allows a fast feedback. Further decreasing the window length to 750, 500, or 250 ms results in performance loss for all subjects.

Fig. 4 shows the three sets of spatial patterns for subject g3 underlying the EEG data of sessions 1, 4, and 5. The contour

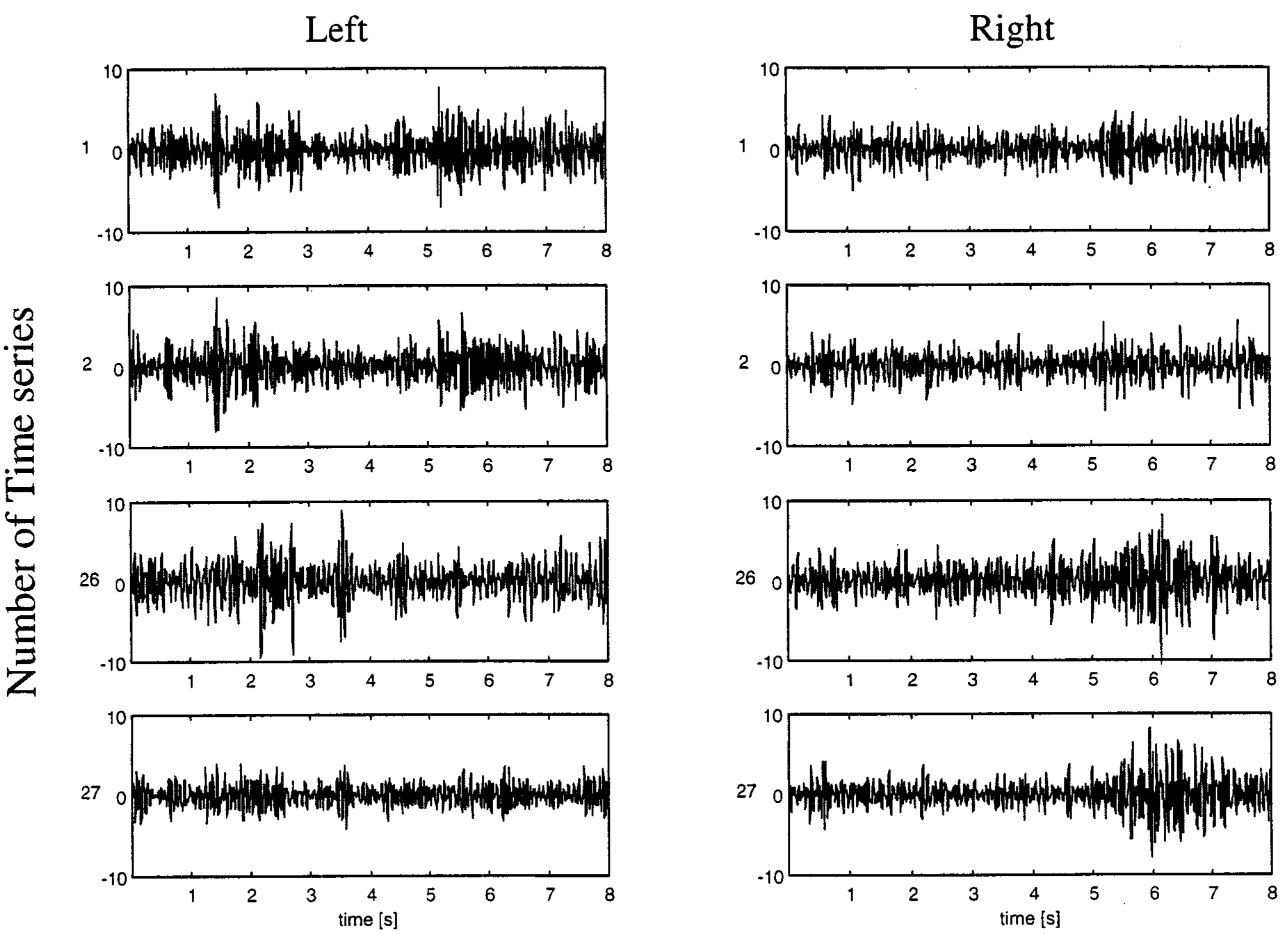

Fig. 5. Time series after filtering with the two most important (1, 27) and two second most important (2, 26) common spatial patterns according to (1). The filter was constructed in such a way that the variance in filter 1 and 2 will be maximized during a left-hand movement imagination and minimized in filter 26 and 27. The left column shows the new time series of a left trial, the right column of a right trial. By comparing the most discriminating time series (1 and 27), a high amplitude difference can be observed. When comparing the second most important time series (2 and 26), still a difference can be seen, albeit a smaller one. The opposite is the case for the right trial. The variance in time series 1 and 2 is smaller than in 26 and 27.

plots were calculated with a cubic interpolation of $\mathbf{W}^{-1}$. The patterns are plotted symmetrically to zero because within a pattern, the coefficients seldomly cross the zero line and only the absolute values of the patterns are important.

Left-hand movement leads to an event-related desynchronization over the contralateral primary sensorimotor area [6]. But at the same time, an increase of the variance over the left hemisphere takes place. The pattern for left movement imagination is focused over electrode C3 in the most important filters of CSP2 and CSP3. However, the focus for filter CSP1 is more posterior. The second most important filters in Fig. 4 show a more fuzzy variance distribution, but the maximum is also near to C3. For right-hand movement imagination, the focus is over C4 in the most important filters of CSP2 and CSP3. CSP1 shows a focus posterior to Cz. The second most important filters show a higher variance posterior to C4 in the case of CSP2 and CSP3 and around C3 at CSP1. Electrodes on the opposite side of the focus have coefficients close to zero. The patterns for the other subjects basically show the same structure.

After applying the most and second most important filter pairs to left and right trials, four new time series were obtained. These temporal patterns for one left- and one right-hand movement imagination are displayed as EEG traces for visual interpretation in Fig. 5.

Then the features obtained from (3) with a 1-s time window were used for further analysis. The classification accuracy was calculated with a 10×10-fold cross-validation of a linear discriminant for 0.5-s steps. The features of the classification time point with the lowest classification error were used to set up the subject-specific weight vector with the linear discriminant analysis (LDA) for the experiments with feedback (see Fig. 3). Table II gives an overview of the best classification time points over subjects and sessions. This off-line procedure, from reading the artifact corrected data from the harddisk until the availability of the new CSPs and WVs, takes about 30 min. The next session can be started immediately after calculation of the CSPs.

On the second day, session 2 was performed with feedback. The 27 EEG channels were filtered with CSP1 in real time (most and second most discriminating filters) as shown in Fig. 6. After filtering, the variances of the resulting four time series were calculated for a 1-s window, normalized, and also log-transformed. The resulting features were classified with WV1. This result was used to control the feedback bar on the monitor. The bar, varying in length, pointed to the left if the output of the linear classifica-

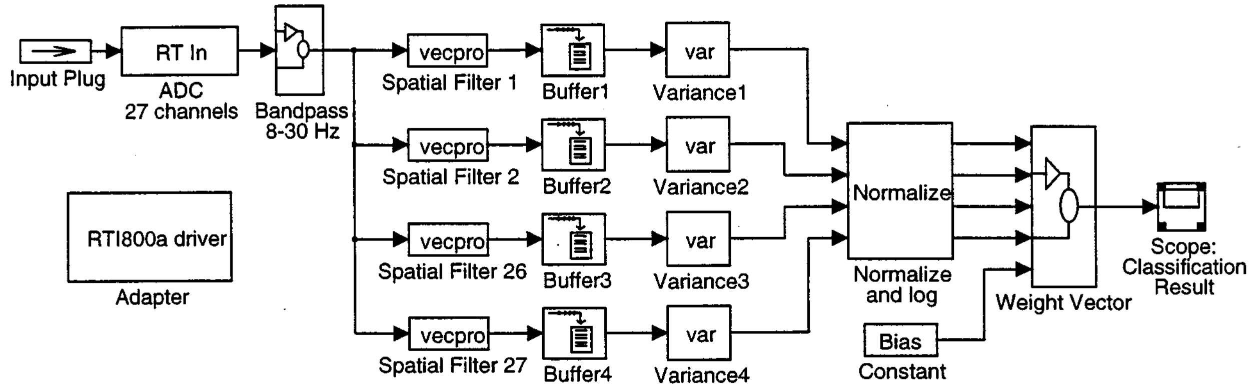

Fig. 6. Simulink model for the real-time analysis of the EEG. A device driver for the RTI800a (DAQ board of Analog Devices) makes the connection to the real world. In this case, the input block represents analog input channels 1 to 28 (EEG#1 to EEG#27, Trigger). Channels 1 to 27 are bandpass filtered between 8 and 30 Hz. The output signal is then passed to the two most (Spatial Filter 1 and Spatial Filter 27) and two second most (Spatial Filter 2 and Spatial Filter 26) discriminating common spatial filters. After temporal and spatial filtering, the variances of the resulting four time series were calculated for a 1-s window, normalized, and also log-transformed. The resulting features were classified with the WV. This result was used to control the feedback bar on the monitor. A detailed description of the hardware and software components is given in [8] and [20].

TABLE II
CLASSIFICATION TIME POINTS (CTPs) OF THE WVs ACCORDING TO SUBJECT AND SESSION. THE WV WAS ALWAYS SET UP FROM THE BEST CLASSIFICATION TIME POINT ACHIEVED WITH A 10 × 10 CROSS-VALIDATION WITH THE ACTUAL CSP. GRAY BOXES INDICATE SESSIONS WITHOUT FEEDBACK

Subject	Session-number	C.T.P. of WV [s]
g3	1	5
	3	5.5
	4	5.5
	5	5.5
g7	1	7
	3	5.5
	4	4.5
	5	5
i2	1	5
	3	5
	4	5
	6	5

tion was positive and to the right if negative. The absolute value of the classification result is a measure of how reliably the side was determined and controlled the length of the bar.

Then session 3 was performed without feedback in order to set up WV2. In session 4, WV2 and CSP1 were used to give feedback. On the third day with the data of session 4, a new CSP2 and WV3 were calculated and used in session 5. Then the update procedure of the CSP and WV was repeated again. It is of importance to point out that for those sessions conducted on the same days, the electrodes were applied only once, thereby minimizing any variations in placement for those sessions.

VI. RESULTS

The time courses of the on-line classification results of the feedback sessions are graphically presented in Fig. 7 for all three subjects. A comparison of on-line error and the 10 × 10 fold cross-validation error calculated off-line is given in Table III. Altogether 13 sessions with feedback, consisting of 160 trials each, were held. Sessions 1 and 3 were performed without feedback, where the subjects were instructed to imagine a right- or left-hand movement right after the cue presentation. These results are not reported in Fig. 7 because the EEG was not classified in real time during these sessions. Sessions 2, 4, 5, 6, and 7 were performed with feedback. The feedback was shown on the monitor from second 4.25 until second 8 and was continuously updated in real time with the CSPs and with the WVs obtained in previous sessions according to Fig. 3.

The on-line classification error ranged from 1.8 to around 50% for all classification time points and subjects. The lowest on-line error rate in the last sessions for g3 was 1.8% (second 5.5), for g7 6.8% (seconds 5 and 5.5), and for i2 14% (second 5). In comparison, the lowest cross-validation error rate for subject g3 was 0% (second 5.5), for g7 6.5% (second 5.5), and for i2 8.7% (second 5) for the same sessions as shown in Table III. The error rate increased slightly by 1.8 0.3, and 5.3%, respectively, with the on-line classification. The reason for the difference is that the on-line result can be biased, meaning the feedback bar on the monitor is pointing slightly more in one direction.

It is important to note that the minimum classification error decreased from 18.8% in the first feedback session to 1.8% in the last session for subject g3, from about 50 to 6.8% for subject g7, and from about 50 to 14% for subject i2.

However, the results from the three subjects show basic differences.

1) Subject g3 achieved an on-line classification error between 18.8 and 31% (between second 4.25 and 8) in the first feedback session. The update of the WV after session 3 decreased the minimum error rate to 14.4% at second 5.5. The update of the common spatial filter and of the WV after session 4 had nearly no effect on the error rate in session 5. The minimum error rate remained constant. But the update of the CSP and of the WV after session 5 caused a decrease of the minimum error rate to 1.8%,

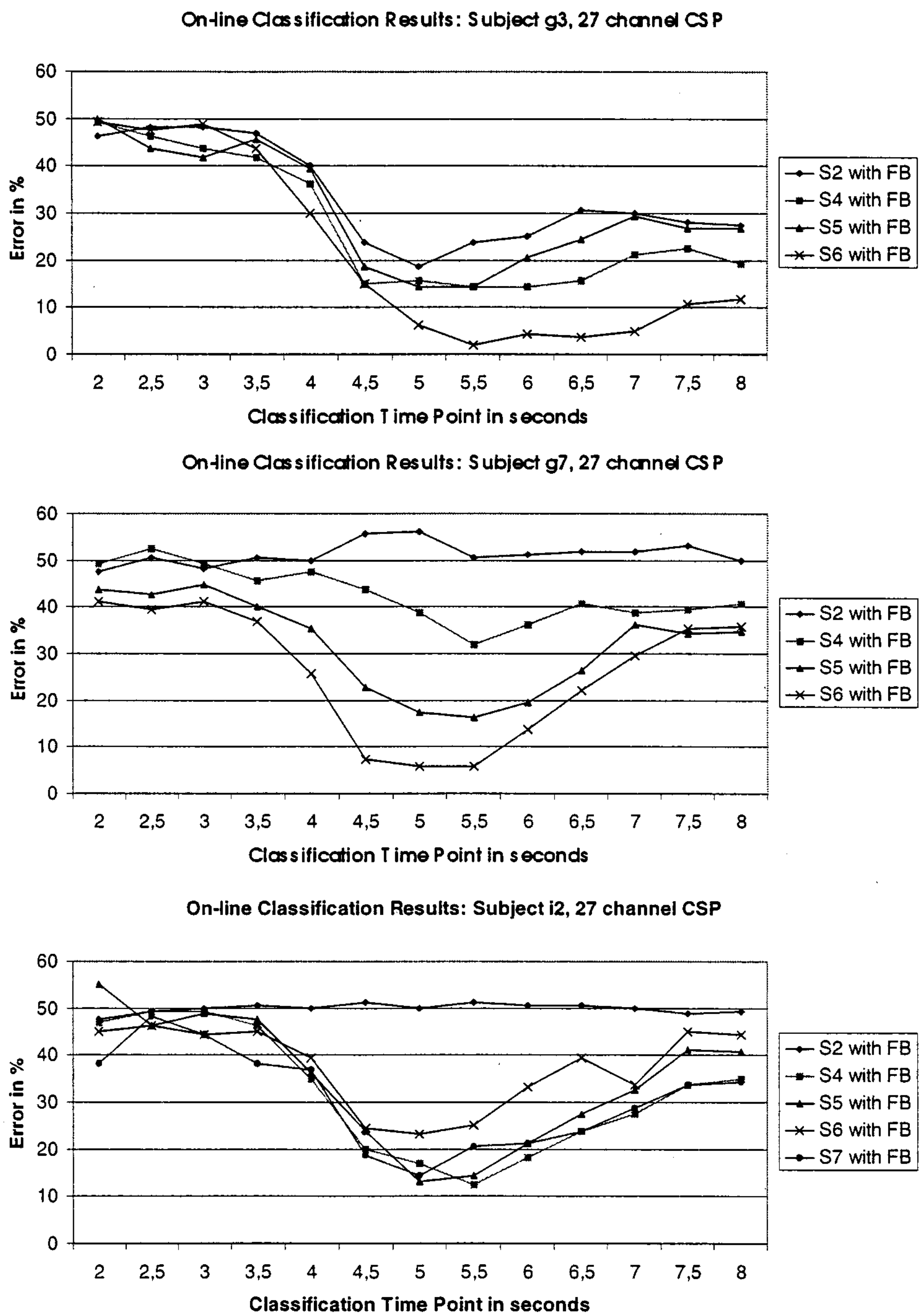

Fig. 7. Time course of the on-line classification error (100% minus accuracy), starting 1 s before visual cue stimulus. Subjects participated in four (g3 and g7) or five (i2) sessions with feedback.

which corresponds to three misclassified trials out of 160. The time points of the minimum error rate always correspond to the calculation time point of the WV, as shown in Table II. Therefore, the best classification time point was always known in advance.

2) Subject g7 was not able to control the feedback bar in session 2. Table III clearly shows the difference between the on-line (around 50%) and cross-validation (32.8%) error rates. The cross-validation shows that the left- and right-hand movement imagination is separable, but the bar was always pointing in one direction. After calculating a new WV from the data of session 3, the on-line error decreased from about 50% in session 2 to 31% (Section 5.5) in session 4. The update of the CSP and of the WV after session 4 clearly decreased the error rate to a minimum of 16.3% (Section 5.5). Similar to subject g3, the calculation of CSP3 and WV4 caused a decrease of the minimum error rate to 6.8% (Section 5 and 5.5). The best classification time point always corresponds to the calculation time point of the WV, except for session 5 (session 2 is not considered). The WV was set up at second 4.5, but the best classification time point was at second 5.5.

TABLE III
THE CROSS-VALIDATION (CV) ERROR RATES FOR SESSIONS WITHOUT (GRAY BOXES) AND WITH (WHITE BOXES) FEEDBACK ARE SHOWN FOR THE BEST CLASSIFICATION TIME POINT. THE ON-LINE ERROR RATES WERE ONLY CALCULATED FOR FEEDBACK SESSIONS. VALUES IN BRACKETS INDICATE ERROR RATES ACHIEVED WITH A CSP THAT WAS SET UP OF THE DATA OF THE SAME SESSION

Session-Number/ Day	g3		g7		i2	
	CV Error [%]	On-line Error [%]	CV Error [%]	On-line Error [%]	CV Error [%]	On-line Error [%]
1/ 1	(4)	-	(10.4)	-	(15.8)	-
2/ 2	13.9	18.8	32.8	50	33.6	50
3/ 2	16.8	-	31.2	-	24.2	-
4/ 2	11.5 (0.4)	14.4	28.9 (9)	31	10.9 (3.4)	12.5
5/ 3	12.8 (0.6)	14.4	14.1 (7.4)	16.3	14	13
6/ 3	0	1.8	6.5	6.8	17.1 (8)	23
7/ 3					8.7	14

3) Subject i2 was also not able to control the feedback bar in session 2. But Table III again shows that the EEG was separable with a cross-validation error of 33.6%. The bar was again pointing in only one direction. The WV update of the data of session 3 decreased the minimum on-line error rate to 12.5% (Section 5.5). In session 5, the same CSP and WV as in session 4 was used. The on-line error rates of both sessions are quite similar. After updating the CSP and the WV with the data of session 4, an increase of the error rate was observed in session 6. Repeating the update procedure of CSP and WV again decreased the minimum error rate to 14% (Section 5). Therefore, performance did not improve with CSP3 and WV4, in comparison to the results in sessions 4 and 5. In sessions 5–7, the best classification time point corresponds with the calculation time point of the WV (session 2 is not considered). In session 4, the best classification time point was 0.5 s later than the classification time point of the WV.

VII. DISCUSSION

This paper demonstrates that the method of common spatial patterns can be used to analyze the EEG in real time in order to give feedback to the subject. The method was utilized to give fast, continuous, and accurate feedback during left- and right-hand movement imagination. Furthermore, the classification accuracy that can be achieved after only three days of training, when the CSP filter is adapted between sessions, was determined. All three subjects were able to reduce their on-line classification error within three days to 2% (g3), 6% (g7), and 14% (i2) in six to seven sessions, respectively. However, it must be pointed out that subjects had participated prior to this study in 23 (g3), five (g7), and seven (i2) BCI sessions using bandpower or AAR parameters for the feedback calculation [2], [8], [16]. Usually one to three sessions were carried out per day, which gives a training period of a few days. Results by Wolpaw and McFarland show that healthy subjects and spinal cord injury patients usually need several months to develop high accuracy (i.e., >90%) using mu and beta frequency components [21]. Also Birbaumer's group reports a training period of several months with slow cortical potentials to achieve accuracies of 65–80% for healthy subjects [22]. ALS patients were trained longer than a year [23]. For practical applications, the training time must be minimized to increase the acceptance of the system and motivation of the BCI operator.

The error rates marked by brackets in Table III clearly show the influence of electrode position variations on different days and day-to-day subject's state variations: On every new experimental day, the electrodes have to be mounted anew. Therefore, the electrode positions can be expected to vary slightly between sessions on different days. The measured ERD pattern of sensorimotor rhythms can be completely different when the electrode position varies by, e.g., 2.5 cm [24].

In session 1, cross-validation errors of 4% (g3), 10.4% (g7), and 15.8% (i2) are achieved if the CSP calculated from session 1 is also used to classify the same data. A loss of performance can be observed in sessions 2, 3, and 4 on the second day, whereby CSP1 from session 1 (first day) was used, but besides changes in the subject's state also the electrode positions were not exactly the same as compared to the first day. After setting up CSP2 from session 4 and classifying the same session, the error decreased again to 0.4% (g3), 9% (g7), and 3.4% (i2). The same trend can be seen in session 5 of subject g3 and g7 and session 6 of subject i2. But the lower classification errors of 0.6% (g3), 7.4% (g7), and 8% (i2) are now in the range of the error rates achieved in the next session, which are 0% (g3), 6.5% (g7), and 8.7% (i2). There are two reasons for this:

1) both sessions were performed on the same day (third day) one after another;
2) the electrode positions were exactly the same for the last two sessions.

Therefore, it is recommended not to apply the electrodes anew after setting up a new CSP for the following feedback sessions. However, further investigation is necessary to determine to which extent the difference in error rates can be attributed to variations in electrode applications and day-to-day subject's state variations. For long-term implications of this BCI approach, EEG data of several sessions can be used for the calculation of the CSP. This allows the generation of a more robust filter in order to overcome the mentioned problems.

The study clearly showed that it is important to update the WV. For example, the reason for the 50% error rate in feedback session 2 for subjects i2 and g7 was a biased classification result, meaning the feedback bar on the monitor was always extending in just one direction. Therefore, the on-line classification error was higher than the cross-validation error. This bias can be eliminated by setting up a new weight-vector.

A disadvantage of the CSP method is the large number of electrodes needed. Thus, extensive electrode application time and multichannel EEG analysis are required. The necessity for, e.g., a 27-channel EEG-amplifier system limits the use of the CSP as a portable BCI system, but it is still wheelchair mountable. Further work is therefore necessary to search for the optimal number of electrodes. An off-line study with the CSP method has shown marginal differences in the classification accuracy of single trials with a binary motor imagery task when 18 electrodes were used, as compared to 56 electrodes [14]. The use of implanted electrodes in the future should solve the problem inherent in precisely applying a large number of electrodes and will provide freedom from muscle and movement artifacts. Experimental setups with implanted electrode arrays are already being investigated [25], [26].

It is also important to remove artifacts for the setup of the common spatial patterns. During on-line operation of the BCI, the spatial pattern performs a weighted averaging of the EEG, and this reduces the artifacts.

The only parameters that must be adjusted for the CSP method are the time segment for the calculation of the CSP and, during on-line processing, the time window for the calculation of the variances. But the selection of these parameters is not very crucial.

An advantage of the CSP method is that it does not require a priori selection of subject-specific frequency bands, as necessary for bandpower or frequency estimation methods [27], [28]. Although AAR parameter estimation methods (such as the recursive least squares algorithm) [2], [8], [29] also do not require a frequency band selection and operate with only two bipolar EEG signals, a cross-validation error of 0% with the AAR model was never achieved. Experiments with the same paradigm and AAR together with the LDA approach resulted in lowest on-line errors for three subjects of 5, 9, and 9% after six to seven sessions (for details, see [8]). Long-term experimental series with two bipolar channels, using delayed feedback that presented the classification result at the end of each trial ("correct" or "not correct") computed with bandpower and learning vector quantization approach, were carried out with four subjects. This type of experiment yielded to minimum on-line classification errors of around 10, 13, 14, and 17% after seven to 14 sessions [2]. A direct comparison of results, however, is not possible, because only trained subjects, who also had participated in former series of experiments, were included in the present study.

We think that the inconvenience of applying more electrodes is rationalized by performance improvements with the method of common spatial patterns and will make a practical difference in patients requiring rehabilitation. One must consider that the most obvious strategy for achieving a higher speed of communication is to reduce the error rate. Even a small decrease of the error rate causes a high increase of the BCI bit rate.

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