Toward Self-Paced Brain–Computer Communication: Navigation Through Virtual Worlds

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***Abstract*—The self-paced control paradigm enables users to operate brain–computer interfaces (BCI) in a more natural way: no longer is the machine in control of the timing and speed of communication, but rather the user is. This is important to enhance the usability, flexibility, and response time of a BCI. In this work, we show how subjects, after performing cue-based feedback training (smiley paradigm), learned to navigate self-paced through the "freeSpace" virtual environment (VE). Similar to computer games, subjects had the task of picking up items by using the following navigation commands: rotate left, rotate right, and move forward (three classes). Since the self-paced control paradigm allows subjects to make voluntary decisions on time, type, and duration of mental activity, no cues or routing directives were presented. The BCI was based only on three bipolar electroencephalogram channels and operated by motor imagery. Eye movements (electrooculogram) and electromyographic artifacts were reduced and detected online. The results of three able-bodied subjects are reported and problems emerging from self-paced control are discussed.**

***Index Terms*—Brain–computer interface (BCI), classification, electroencephalogram (EEG), motor imagery, self-paced operation mode, virtual reality (VR).**

I. Introduction

For severely paralyzed people, or patients in a "locked-in" state, direct brain–computer interaction provides one method of reestablishing communication. A brain-computer interface (BCI) recognizes voluntary changes in ongoing brain activity and translates different mental states into appropriate commands for communication and control. For a review on BCI technology see, for example, [1]; for taxonomy, see [2].

The majority of BCIs used these days are designed for synchronized (or cue-based) operation which means that the timing and speed of communication are preset by the paradigm. This, however, does not represent a natural way of interaction. In fact, a BCI should be able to detect if the user 1) intentionally decides to start and stop performing specific mental tasks [intentional control (IC)] or is 2) not generating commands [noncontrol state (NC)] (e.g., periods of thinking, daydreaming, or reading). Such self-paced BCIs are constantly classifying the ongoing brain activity and are therefore always available for control [3]. Recently, an increasing number of papers started to address this type of operation paradigm [4]–[9].

In this work, we present the new two-classifier integrated three-class motor-imagery (MI)-based Graz–BCI [10], designed for self-paced operation and controlled by analyzing three bipolar electroencephalogram (EEG) channels only. With the combination of two classifiers, classifier CFR1 is set up to discriminate between different MI tasks and classifier CFR2 is trained to detect any MI-related brain activity in the ongoing EEG, we create a system that is able to discriminate between several MI-modulated mental states (IC) and NC.

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II. Methods

A. Toward Self-Paced Operation: Training Procedure

1) cue-based training without feedback. Evaluation of subject-specific brain patterns by collecting 22 monopolar channel EEG of left-hand, right-hand, foot, and tongue MI trials;
2) selection of three bipolar channels, three MI tasks, and setup of classifier CFR1;
3) cue-based three-class feedback training using CFR1 until the online classification accuracy was $>75\%$;
4) setup of classifier CFR2 (MI versus NC) after identifying relevant EEG features;
5) cue-based feedback training with longer intertrial intervals (longer periods of NC);
6) self-paced feedback training and evaluation.

B. Subjects and Data Acquisition

Based on data sets of eight subjects, which took part in the training without feedback experiment, those three subjects with the visually most discriminative event-related (de)synchronization (ERD/ERS) time–frequency patterns [24] were selected to continue feedback experiments. The selected subjects v4, v9, and x6 (2 male, 1 female, right handed, age 24$\pm$ 1.9 yr) previously participated in [11] and learned, after three feedback training sessions, to operate a cue-based two-class BCI with a classification accuracy of 71.4%, 82.8%, and 86.4%, respectively.

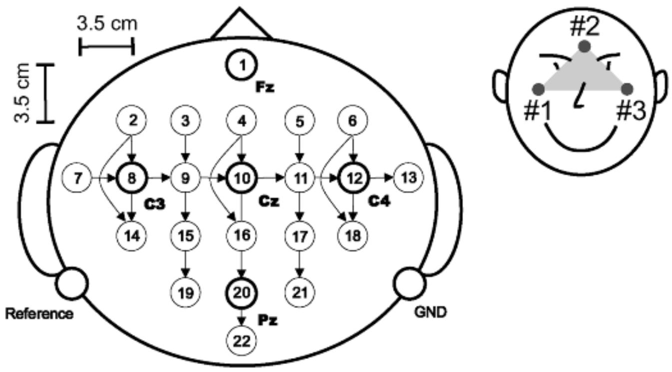

Fig. 1. EEG and EOG electrode placement. For both, reference was placed on the left and ground on the right mastoid. The arrows between EEG electrodes show the analyzed bipolar derivations ($\oplus \rightarrow \ominus$).

Two different electrode arrangements were used. For the training without feedback, 22 monopolar EEG channels (Ag–AgCl electrodes, extended 10–20 system, reference left mastoid, ground right mastoid) were recorded; Feedback experiments were performed using three bipolar EEG channels only (ground Fz). In addition, three electrooculogram (EOG) channels were acquired (Fig. 1). The signals were amplified, analog filtered between 0.5 and 100 Hz, and recorded with a sample rate of 250 Hz.

C. Signal Processing

1) Graz–BCI: Band-power (BP) features were estimated from the ongoing EEG by digital bandpass filtering (fifth-order Butterworth), squaring, and averaging (moving average) the samples over the last second. For classification, Fishers linear discriminant analysis (LDA) was applied to the logarithm of the BP estimates. Feature extraction and classification were computed at the rate of data acquisition (sample-by-sample). Visual feedback was updated at 25 Hz.

The fully automated correction method introduced in [12] was used to reduce the influence of EOG artifacts. EMG activity was detected by applying the inverse filtering method [13]. Each time the root mean square (rms) of the inversely filtered process exceeded the detection threshold of $5 \cdot \mathrm{RMS}$ from artifact-free EEG, a warning was presented on the screen for 1 s [Fig. 2(B)]. Subjects were instructed to relax (loosen the musculature) and make the warning disappear in order to continue with the task. A time-invariant autoregressive model (model order 11), whose parameters are the coefficients of a digital filter, was used to model artifact-free EEG. Therefore, 2 min of artifact-free EEG was recorded at the beginning of each feedback session during which subjects were instructed to sit relaxed and not move.

2) Feature Selection: Distinction sensitive learning vector quantization (DSLVQ), an extended version of Kohonen's learning vector quantization algorithm (LVQ), was used to identify the most informative features [14]. LVQ uses a reduced number of labeled reference vectors (codebook) to approximate the optimal Bayesian decision borders between different classes. Each sample is classified according to the label of its closest codebook vector according to a distance function; the influence of each feature on the distance function is equal. DSLVQ introduces a weighted distance function which rates

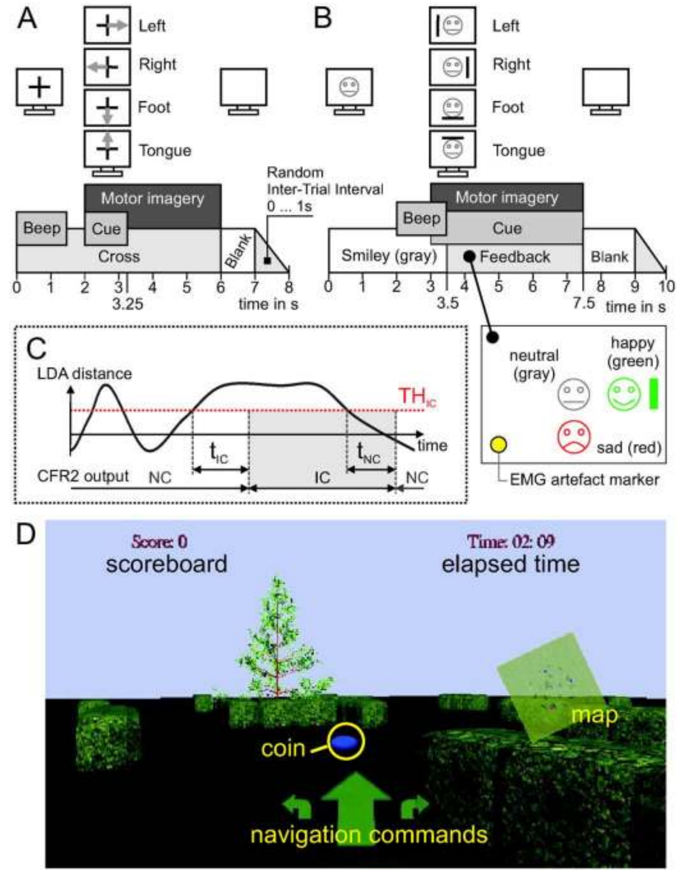

Fig. 2. (A) Cue-based training without feedback paradigm. (B) Cue-based feedback training paradigm. (C) Switch between intentional control (IC) and noncontrol (NC). (D) Screenshot of the "freeSpace" virtual environment. A tree, some hedges, and a coin (to collect) are visible. The big arrow shows the chosen navigation command (detected MI pattern); here, it is forward movement. During NC, the three arrows had the same (small) size.

the influence of the features for classification: the most informative features are upgraded while features that contribute to misclassification are discarded. The LVQ codebook splits the classification problem into subproblems. By finding an optimal linear approximation for the subproblems, the relevance of the features, which determines the correct classification, is analyzed. The major advantage of DSLVQ is that it does not require expertise nor any *a priori* knowledge or assumption about the distribution of the data. Furthermore, not only are relevant features identified, but feature combinations are also [14].

In order to obtain a reliable feature relevance RT_n [14], the DSLVQ method was repeated 100 times (three codebook per class, type C training, 10 000 iterations, learning rate decreased from $\alpha = 0.05$ to $\alpha = 0.0$ and $\alpha'(t) = 0.1 \cdot \alpha(t)$). For each repetition, randomly selected 50% of the BP features were used for training and the remaining 50% were kept to test the DSLVQ classifier.

D. Classifier CFR1: Design and Customization

The three-class problem (number of classes $N_C = 3$) was solved by applying majority voting to three pairwise-trained LDAs (see [6] for details). In contrast to [6], however, only the sign of the LDA output was considered (<0 class 1, $\geq$0 class

2). The class with the highest frequency of occurrence (f_{occ}) within the past subject-specific N samples (maximum N=75 or 250 ms) was selected and a normalized distance d_n was computed

$$d_n = \left(f_{\mathrm{occ}} - \frac{N}{N_C}\right) / \frac{(N_C - 1) \cdot N}{N_C} \forall f_{\mathrm{occ}} > \frac{N}{N_C}, \quad \text{or}$$
$$d_n = 0 \forall f_{\mathrm{occ}} \leq \frac{N}{N_C}.$$

This normalization prevents quick changes of the classification result and enables a smooth transition ("zero'" crossing) between class-specific feedback. The disadvantage is the introduction of an additional feedback delay.

1) Training Without Feedback: The 22 monopolar EEG channel setup was used (Fig. 1). Subjects were instructed to perform continuous kinesthetic [15] left-hand, right-hand, foot, or tongue MI according to the instructions presented on the screen. The kind of movement was chosen by the subject depending on his/her preferences (e.g., playing a piano or swimming) and fixed before the recording started. Two sessions were recorded for each subject on different days. Each session consisted of six runs with 48 trials each (12 trials per class per run). Subjects had to perform the task of randomly selected MI for 4 s. The intertrial interval was about 5 s. Fig. 2(A) summarizes the paradigm timing.

2) Feature Selection: For each subject, individual 4-class DSLVQ analyses were performed with BP features extracted with the same time lag Δt to cue presentation ($\Delta t = 0.0 : 0.5 : 4.0$ s). For each Δt from each trial and each of the examined 23 bipolar channel derivations (Fig. 1), 15 nonoverlapping BP features between 6–36 Hz with a bandwidth of 2 Hz were computed. The selected frequency range is relevant for the classification of MI [16]. By selecting 2-Hz frequency bands, the resulting temporal delay (blur) and spectral resolution is acceptable. At the same time, the total number of features was limited in order to avoid overfitting effects.

The most relevant BP features were selected by evaluating the RT_n values from the DSLVQ analysis at Δt with the highest classification accuracy. BP features were selected manually according to the following criteria: 1) large mean RT_{n0} value and small variance, 2) maximum number of bipolar channels $= 3$, 3) maximum number of BP features $= 6$, and 4) symmetrically arrangement over sensorimotor areas (hemisphere). Two adjacent BP features were combined to one 4-Hz BP feature (e.g., 10–12 Hz and 12–14 Hz to 10–14 Hz).

With the features identified for each three-class MI combination, an independent CFR1 was trained and a sample-by-sample online simulation was computed (10×10 cross-validation). The three MI tasks with the best classification accuracies within the feedback period were selected for online experiments.

3) Feedback Training: Online experiments were realized using the three subject-specific bipolar EEG derivations. Each session started with unguided practice (free training) that lasted for about 5 min. During this period, subjects could test the classifier (continuous feedback) and the smoothing parameter N (for d_n) was adjusted according to the subjects' preference (slow or fast reaction time). The feedback presented to the subjects was a smiley [see Fig. 2(B)]. Five (subjects v4 and x6) and seven (v9) feedback sessions were recorded with at least four (max. 6) runs of 30 trials each (ten per class). Subjects were given the task of moving the gray-colored smiley, initially positioned in the center of the screen, according to the cue to the left/right/down(up) by performing left-hand, right-hand, or foot (tongue) MI, respectively [see Fig. 2(B)]. The smiley changed to color green and was happy when moved to the correct direction; otherwise, the smiley was red and sad [Fig. 2(B)].

After each session, feature selection was performed and the classifier was updated. Each time, the accuracy of the updated classifier was higher than the online result, subjects tested the new classifier during the unguided practice period of the next session. When subjects achieved better BCI control, the updated classifier was used for feedback experiments.

E. Classifier CFR2: Design and Customization

One single LDA function was trained to discriminate between IC (three MI tasks merged) and NC.

1) Feature Selection: In order to obtain a more detailed spectral representation, 31 BP features (1-Hz overlap) between 6–36 Hz with a bandwidth of 2 Hz were extracted from each channel and analyzed by DSLVQ. The six most relevant features were selected to set up the LDA.

From each trial of the last cue-based feedback training session (four runs with 30 trials), two BP feature vectors were extracted from the feedback interval around the best online classification accuracy (e.g., best classification at $\mathrm{t} = 5.5$ s; BP extracted at $t_1 = 5.5$ s and $t_2 = 6.5$ s) The resulting 4 runs $\cdot$ 30 trials $\cdot$ $2\ \mathrm{BP} = 240$ BP samples were defined as IC. NC consisted of 120 BP samples extracted equidistantly from the 2-min EEG block used to set up the EMG detection algorithm. Furthermore, 120 feature samples were extracted from each trial at $\mathrm{t} = 3.0$ s (before cue presentation). The latter time was selected with the intention to detect only MI specific patterns during feedback (after cue presentation) and not unspecific activations (e.g., expectation) induced by the appearance of the fixation cross.

To make the CFR2 more robust and reliable, considering the nonstationarity and inherent variability of brain signals, one threshold ($\mathrm{TH_{IC}}$) and two transition periods, one for the state switch NC to IC (t_{IC}) and one for IC to NC (t_{NC}), were introduced. Each time the distance between the BP features to classify and the optimal LDA hyperplane was higher than $\mathrm{TH_{IC}}$ for t_{IC}, the IC state was detected. Whenever the LDA distance did fall below $\mathrm{TH_{IC}}$ for t_{NC}, NC was detected [see Fig. 2(C)]. The BCI reaction time was modified by t_{IC} and t_{NC}; changing $\mathrm{TH_{IC}}$ meant moving the decision hyperplane toward IC or NC. The initial $\mathrm{TH_{IC}}$ used for the feedback experiment was computed by receiver operator characteristic (ROC) analysis. The value which maximizes the number of TP detections within the feedback period and, at the same time, minimizes the number of FP detections anywhere else was selected (sample by sample).

The output of the BCI was triggered by CFR2. Each time IC was detected, the classification result of CFR1 was feed through. Otherwise, the output was "zero."

2) Feedback Training With Longer Intertrial Intervals: Two sessions with five feedback training runs (ten trials per class) were performed. The first two runs consisted of feedback training with CFR1 only (Section II-D3) to monitor the subjects' actual performance. Thereafter, subjects underwent an unguided practice lasting about 10 min to determine $\mathrm{TH}_{\mathrm{IC}}$, t_{IC}, and t_{NC}. Depending on the statements of the subjects, $\mathrm{TH}_{\mathrm{IC}}$ was gradually increased or decreased. The criteria was that subjects were able to control the smiley but, at the same time, the number of FP detections was at a minimum. The transition times were set to 500 ms and also gradually adapted if required. A maximum period of 1 s was chosen for t_{IC} and t_{NC}. Subjects had to identify these values by themselves empirically. The values found were fixed and remained unchanged during the remaining experiments of each session.

To train subjects to gain self-paced control, the feedback smiley paradigm from Section II-D3 was modified. The feedback smiley was presented and reactive during the whole run. Each run consisted of 30 trials (ten per class). From $\mathrm{t} = 0.0$ s to $\mathrm{t} = 8.0$ s, the cue was presented and subjects were given the task of stirring the smiley in the indicated direction. After this period, a random intertrial period between 7.0 s and 17.0 s was presented (NC). At the beginning, a gray smiley was positioned in the middle of the screen. During the transition times t_{IC} or t_{NC}, the color of the smiley changed gradually from gray to green or green to gray, respectively. In addition, the smiley moved according to CFR1 with the distance d_n weighted by the normalized transition time (from 0 to 1). In this way, subjects were informed of a forthcoming state switch.

After the first session, an additional DSLVQ analysis was performed for CFR2. Subjects tried the new CFR2 during the unguided practice period of session two and if the performance increased, the new classifier was used.

F. Evaluating Self-Paced Control of CFR1 and CFR2

1) "Freespace" Virtual Environment: The virtual environment (VE) was created using the 3-D modelling software package Maya (Alias Wavefront, Toronto, ON, Canada). Furthermore, it was animated (collision detection) and visualized by the Qt application framework (Trolltech, Oslo, Norway). The virtual park, size 30 × 30 units, consisted of a flat meadow, several hedges, and a tree placed in the middle for orientation. Three items (coins) were positioned on fixed predefined locations inside the park. Three navigation commands were implemented: rotate left, rotate right (angular velocity $45°/s$), and move forward (speed 1 unit/s). With this control, each part of the park could be reached. To help subjects not get lost and facilitate locating the coins, a map of the VE, showing the actual position, was presented [see Fig. 2(D)]. Interaction with each existing virtual object was possible. A sphere, representing the user in the VE, was used for collision detection. Each time the surfaces of two objects intersected, an event was generated: Coins were collected and hedges or the tree had to be bypassed.

2) Experimental Paradigm: Two sessions were recorded on two different days. Each session started with about 20 min of unguided practice (free training). Subjects could get familiar with the freeSpace VE and the navigation mechanism. $\mathrm{TH}_{\mathrm{IC}}$ was adapted and fixated if required.

The VE was presented to the subjects in the first-person-view on a conventional computer screen [Fig. 2(D)]. Subjects were assigned the task of picking up the three coins within 3 min. From a randomly selected starting point (different positions for each run but the same positions for all subjects), subjects could explore the park in the following way: left-/right-hand MI resulted in a rotation to the left/right whereas foot or tongue MI resulted in a forward motion. No action was performed whenever NC was detected.

TABLE I
DSLVQ ANALYSIS. FOR EACH SUBJECT (ID), THE IDENTIFIED MOTOR IMAGERY (MI) TASKS, BIPOLAR CHANNELS (BIPCH), AND BAND POWER FEATURES (IN HERTZ) FOR CFR1 AND CFR2 ARE PRESENTED

ID	MI	BIBCH	CFR1	CFR2 (IC vs. NC)
v4	Left	+02-14	11-13, 25-27	12-14, 15-17, 20-22, 25-27
	Right	+04-16		9-11, 21-23
	Tongue	+06-18	11-13, 23-25	
v9	Left	+02-08	11-13, 12-14	12-14, 19-21, 27-29
	Right	+04-16	11-13, 12-14	9-11, 11-13
	Foot	+06-12	11-13	21-23
x6	Left	+02-08	10-12	8-10, 16-18
	Right	+04-10	9-11	8-10
	Foot	+06-12	10-12, 19-23	15-17, 24-26

Six self-paced feedback training runs of 3 min each were performed. The first three runs served as training, runs four to six were used to evaluate the performance. For each subject, the distance covered and resulting path depended on the individual routing strategy (e.g., pickup order) and the ability to operate the BCI. At the end of each session, subjects were asked to self-report on the BCI performance.

III. RESULTS

The results presented in this work are sample-by-sample based. For each subject, the percentage of samples classified as an EMG artifact was less than 0.9%. In addition, power spectral densities were computed for each channel and checked for muscle activity.

As expected, the α band substantially contributes to CFR1 (Table I). The achieved online performance is shown in Fig. 3(A). The curves show the mean classification accuracy of the four runs recorded at the beginning of the two feedback training sessions with longer intertrial intervals (see Section II-E2). The maximum classification accuracy (mutual information in bit [17]) was 83% (1.07), 88% (1.54), and 80% (0.87) for subject v4, v9, and x6, respectively.

A. Classifier CFR2

Column CFR2 in Table I lists the BP features found by DSLVQ which most discriminate between IC (left hand, right hand, and foot or tongue pooled together) and NC. Offline classification accuracies of 77%, 84%, and 78% for subject v4, v9, and x6, respectively, were computed (10 × 10 cross-validation).

The classification performance for CFR1 and CFR2 during the feedback training with longer intertrial intervals days is presented independently. The mean classification accuracy of CFR1 during the active period is shown in Fig. 3(B). Compared with the results in Fig. 3(A), similar characteristics can be observed. The mean latency from cue presentation to a classification performance of better than random was about 2 s. For subject v4 and x6, the mean classification accuracies were 75%

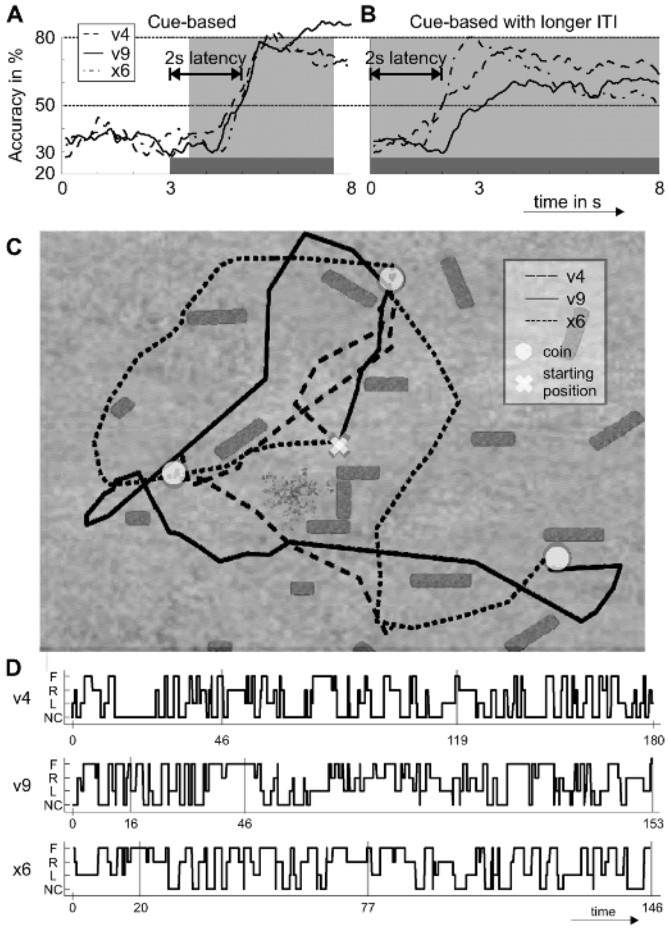

Fig. 3. (A) Mean CFR1 classification accuracy. (B) Mean CFR1 classification accuracy of cue-based feedback training with longer intertrial intervals (ITI). (C) Map of the freeSpace virtual environment showing the best performance (route) for each subject. Subject v9 and x6 successfully collected each of the three coins; Subject v4 collected only 2 coins. (D) BCI classification output for the routes shown in B. ($\mathrm{L} =$ r rotate left, $\mathrm{R} =$ rotate right, $\mathrm{F} =$ move forward, $\mathrm{NC} =$ noncontrol.)

and 80%, respectively; for v9, the mean classification accuracy was 60%.

As performance measures true positive (TP) and false positive (FP), rates were computed for CFR2. The evaluation criteria for TP and FP were very strict: According to the feedback paradigm, samples from $\mathrm{t} = 0.0$ s to $\mathrm{t} = 8.0$ s, the period of cue presentation, were defined as IC and labeled as class 1. The remaining samples were NC labeled as class 2. Since cognitive processes (e.g., processing the visual cue, motor preparation, decision making) as well as digital signal processing requires time, and according to the time latency of about 2.0 s, an additional evaluation with TP defined from $\mathrm{t} = 2.0$ s to $\mathrm{t} = 10.0$ s was computed. The TP/FP rates were computed by dividing the number of correctly classified samples within the TP/FP intervals by the total number of samples belonging to the TP/FP class. Table II summarizes these results. Mean FP rates (over subjects and sessions 2-h NC and 1-h IC) of 19.1% or 16.9% could be achieved. The mean TP rates for the 8-s action period were 25.1% or 28.4%. Column T_{IC} in Table II shows the number of transitions from NC to IC during the cue presentation. Subjects succeeded in 18.6 of 30 trials to switch from NC to IC. The

TABLE II

CFR2 PERFORMANCE. THE DURATION IN SECONDS (DUR.), THE NUMBER OF TRANSITIONS FROM NC TO IC (T_{IC}, MAX. 30/RUN), AND TP/FP DETECTION RATES FOR EACH SESSION AND RUN (S-R) AND SUBJECT (ID) ARE LISTED. FURTHERMORE, SESSION MEANS $\overline{s_1}$ AND $\overline{s_2}$ ARE REPORTED

				0.0-8.0		2.0-10.0		
ID	S-R	Dur.	T_{IC}	TP	FP	TP	FP	t_{NC}
v4	1-1	602	13	18.4	16.9	20.0	15.8	362
	1-2	609	10	7.6	7.2	9.8	5.8	369
	1-3	615	16	17.8	12.2	21.1	10.1	375
	$\overline{s_1}$	*609*	*13*	*14.6*	*12.2*	*17.0*	*10.6*	*369*
	2-1	612	27	32.7	22.5	36.9	19.5	372
	2-2	612	29	33.5	23.5	37.1	21.2	372
	2-3	610	28	39.7	23.2	33.7	27.0	370
	$\overline{s_2}$	*611*	*28*	*35.3*	*23.1*	*35.9*	*22.6*	*371*
v9	1-1	608	20	24.1	16.6	32.9	10.8	368
	1-2	603	21	32.3	31.4	38.4	27.3	363
	1-3	636	21	23.4	8.8	31.6	3.8	396
	$\overline{s_1}$	*616*	*21.7*	*26.6*	*18.9*	*34.3*	*20.0*	*376*
	2-1	611	13	16.8	14.8	22.8	11.0	371
	2-2	620	20	38.7	24.5	43.1	21.7	380
	2-3	617	18	36.9	32.5	42.1	29.1	377
	$\overline{s_2}$	*616*	*17*	*30.8*	*23.9*	*36.0*	*20.6*	*376*
x6	1-1	602	16	22.1	11.6	21.4	12.0	362
	1-2	606	16	14.5	10.5	16.7	9.0	366
	1-3	608	15	16.1	15.7	19.2	13.6	368
	$\overline{s_1}$	*605*	*15.7*	*17.6*	*12.6*	*19.1*	*11.5*	*365*
	2-1	628	14	38.1	32.5	39.8	31.4	388
	2-2	632	18	18.9	16.2	19.6	15.8	392
	2-3	614	19	20.2	22.8	24.6	20.0	374
	$\overline{s_2}$	*625*	*17*	*25.7*	*23.8*	*28.0*	*22.4*	*385*
mean		613.6	18.6	25.1	19.1	28.4	16.9	373.6
std		9.9	5.3	9.8	8.0	10.0	8.2	9.9
median		611.5	18.0	22.8	16.8	28.1	15.8	371.5

last column of Table II shows the time in seconds of NC for each run.

B. "FreeSpace" Paradigm

The "freeSpace" experiment performance is summarized in Table III (best results are emphasized). The distance covered, number of collected items, and pickup times are shown for each of the 3 runs and 2 sessions. Subject v9 and x6 were able to collect the three items within the 3-min time limit. Subject v4 was able to collect only two out of the three coins. While v4 and v9 could improve their performance (distance and collected items), the results of session two for x6 were poor compared to the first.

The routes of the best run for each subject are presented in Fig. 3(C). The best results were achieved from each subject independently when starting from the same initial position. The paths show that each subject chose a different way to collect the coins. Fig. 3(D) shows the corresponding BCI classifier output (navigation commands) sent to the VE. The distribution of the BCI classification output is summarized in Table IV. Since subjects were not instructed to self-report erroneous navigation control signals (lucky errors) detected by the BCI which contribute to the collection of the coins, a "random walk" navigation was simulated to estimate the influence of randomness. When beginning from the starting position in Fig. 3(C) and randomly sending MI states or NC to the VE, we obtained a zig-zag-shaped route. The resulting course, however, is unidirectional. Accordingly, it was impossible to collect all three coins within the selected time limit without IC. The same results were obtained by increasing the frequency of occurrence of foot MI.

TABLE III
"FREESPACE" PERFORMANCE. FOR EACH SUBJECT (ID), RUN (R) AND SESSION, THE DISTANCE COVERED (DIST.), AND NUMBER OF COLLECTED ITEMS WITH PICKUP TIMES [#ITEMS (TIME)] ARE SHOWN

		Session 1		Session 2	
ID	R	Dist.	#items (time)	Dist.	#items (time)
v4	1	317	0	1172	**2 (0:46, 1:59)**
	2	544	1 (1:37)	523	0
	3	234	0	963	2 (0:53, 2:59)
v9	1	1223	2 (0:58, 2:21)	1781	**3 (0:16, 0:46, 2:33)**
	2	1573	1 (2:12)	1788	2 (1:10, 2:20)
	3	1438	1 (0:53)	1478	2 (0:39, 2:00)
x6	1	1520	2 (1:49, 2:34)	544	1 (2:19)
	2	1729	2 (0:41, 1:23)	807	1 (0:24)
	3	1635	**3 (0:20, 1:17, 2:26)**	468	1 (0:55)

TABLE IV
FREQUENCY OF OCCURRENCE IN PERCENT OF DETECTED LEFT HAND (L), RIGHT HAND (R), FOOT OR TONGUE (F/T) MOTOR IMAGERY, AND NONCONTROL (NC) FOR EACH SUBJECT (ID), RUN (R), AND SESSION

		Session 1				Session 2			
ID	Rn	L	R	F/T	NC	L	R	F/T	NC
v4	1	18	18	6	58	**14**	**19**	**21**	**46**
	2	14	17	10	59	14	20	15	51
	3	7	4	4	85	16	22	18	44
v9	1	16	12	27	45	**25**	**19**	**36**	**20**
	2	20	18	29	33	17	26	33	24
	3	20	26	30	24	14	13	30	43
x6	1	30	24	39	7	4	8	10	78
	2	27	23	43	7	5	6	14	75
	3	**20**	**22**	**38**	**20**	4	4	9	83

For comparison, the shortest possible route was also computed. With 100% classification accuracy, approximately 110 s were necessary to collect the three items.

The navigation strategy that is selected required that subjects were able to control at least two mental states: Either left or right for rotation and foot/tongue to move forward. The BCI classification output in Fig. 3(D) and the distribution in Table IV, however, show that all four classes occurred. Interviews with the subjects confirmed that all four mental states were deliberately used to navigate through the freeSpace. It was necessary that no navigation command was sent to the VE during non-MI-related mental activity, such as, for example, orientation or routing, or whenever subjects needed a break. For subject v4 and v9, the percentage of navigation commands increased from session 1 to session 2. Although subject x6 was satisfied with the achieved BCI control during the unguided practice period of session 2, a clear bias toward NC is visible during the evaluation.

IV. DISCUSSION

Self-paced control, artifacts processing, reliable classification, or a fast setup are some of the key issues which contribute to making BCIs become a real alternative communication channel.

Online EOG reduction and EMG detection were used for the first time in our feedback experiments. The muscle detection algorithm has been used to identify possible muscle activity in real time. Accordingly, it is possible to use this information to avoid the classification of artifact data. A threshold value can be used to modify the sensitivity and specificity of the detector. An open and interesting issue is the discussion on the desired system response. One can think, for example, of a "system freeze" or "pause mode."

The feedback training results show that three bipolar channels provide enough information to control a cue-based three-class BCI with an accuracy of 80%. Reducing the number of EEG channels is important because of 1) an increase of the usability (less time needed for electrode placement) and 2) a minimization of electrode failures (e.g., exact position on the scalp, impedance, ...). Adaptation to subject-specific parameters is crucial to obtain a reliable classification in a short space of time. By default, DSLVQ was applied and features were manually selected. In the future, this task should be fully automated or adapted online (e.g., [18]).

A new type of feedback was presented to subjects during the feedback experiments. The smiley was introduced because of the "richer" visual feedback (colors, position, shape of the mouth) compared to the bargraph or basket feedback [19], [20]. The expectation was increased motivation for the subjects resulting in improved performance. Interviews with the subject confirmed that the motivation to make the smiley happy was high.

One very important issue for self-paced BCIs is the evaluation criteria or measure of performance. We presented TP and FP rates computed on a sample-by-sample basis from the data collected using a synchronized protocol with longer intertrial intervals. For each subject, the very first attempts of self-paced control were evaluated. The achieved average FP rates of 16.9%/19% (18.9/21.3 min out of 112 min of NC) were to high and the mean TP rates of 28.4%/25.1% to low. During 18.6 out of 30 trials (62%), however, subjects succeeded in switching from NC to IC. One can assume that the longer feedback training period helps to increase the performance. TP/FP rates, however, depend strongly on the definition of the TP and FP intervals. The fact that MI-induced changes in EEG activity are not time-locked and have a variable duration makes a definition difficult. One problem emerging from the cue-based design might be the expectation of the next cue to come. This expectation can unintentionally induce subjects to change the brain activity and produce FP. Nevertheless, we are confident that the sample-by-sample based TP/FP rates are most suited to characterize self-paced BCI performance. To compute correct TP/FP rates, it is necessary to assess the subjects "real" intend and compare it with the BCI output. This information, however, is not directly accessible. One option to obtain this information might be an interactive experimental design, where subjects autonomously determine the timing and type of MI and give immediate feedback (e.g., by interview or by pressing a button, concerning the correctness of the BCI output). When working with severely paralyzed people, however, motor interaction may be impossible.

Compared to CFR1, CFR2 was sensitive to the nonstationarity of EEG. By adapting the detection threshold $\mathrm{TH_{IC}}$, this was taken into account. Higher values of $\mathrm{TH_{IC}}$ cause a decrease of FP; however, the motivation of the subjects might decrease also because generating TP is more difficult. On the other hand, small values result not only in many TPs, but in FPs as well. The varying TP/FP rates in Table II reflect this relationship. For the training, this implies starting with lower values which can be increased when subjects achieved reliable control. When doing so, however, at the beginning of the training, poor TP performance is achieved. Gaining BCI control is not only dependent on machine learning, but psychological aspects also play an important role.

The "freeSpace" paradigm introduced is motivating, entertaining, and most important, it gives an ample scope on how to achieve the goal. Each subject succeeded in navigating through the VE and collecting coins. As can be seen from the distribution of the BCI classification result (Table IV) and having emerged from the interviews, for navigation, both MI and NC were used. The paths in Fig. 3(A) show that each subject choose his own way through the freeSpace. Subject v4 and v9 could improve the performance from the first to the second session. This was not possible for subject x6. Also, during the training, x6 had a high variability of the performance. The overall trend, however, was toward higher classification accuracies. At this stage, the NC state was not explicitly tested. However, as stated by the subjects, periods of NC were important. For further experiments, the paradigm can easily be enhanced by, for example, adding predefined periods of NC.

Although the "freeSpace" VE was implemented for three-dimensional (3-D), stereoscopic representation, at this stage, only a conventional computer screen was used for visualization. One possible option for the future is to train users to operate BCI-based devices (e.g., wheelchair) in the virtual reality [21].

One drawback of defining IC by merging data from three MI tasks was that CFR2 had a "preference" (bias) for certain MI patterns. This behavior was not visible during the evaluation experiments. After the first freeSpace experiments, however, subjects stated that switching into the IC state was easier for certain MI patterns. Therefore, one strategy developed by subjects was to switch into IC by performing the preferred MI first and thereafter switching to the desired one. In Table IV as well as in Fig. 3(D), the preference of right-hand MI of subject v4 is visible. LDA and BP features are a good choice for the discrimination between different MI tasks. The question is whether this classifier/feature is best suited to identify MI patterns in the ongoing EEG. Finding proper methods is one important task for future research. Wavelet-packet analysis [22] or phase relationships [23] may contribute to solve this problem.

V. Conclusion

The methods and training procedure presented in this work enabled selected users to gain self-paced control of a motor imagery-based BCI by analyzing three bipolar EEG channels only. In order to ensure that no muscle activity was used for control, EMG was detected and reported to subjects online; furthermore, online EOG artifact reduction was used. Finding a proper evaluation method (performance measure) is still an open issue. Actually, however, the BCI community is addressing this important topic [3].

The study showed that subjects successfully navigated through the freeSpace VE and collected coins by autonomously switching between different mental states. In doing so, each subject chose the way independently. These are further steps which help BCIs become a real alternative to standard communication channels.

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