Brain-Computer Communication: Motivation, aim and impact of exploring a virtual apartment

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***Abstract*— The step away from a synchronized or cue-based Brain-Computer Interface (BCI) and from laboratory conditions towards real world applications is very important and crucial in BCI research. This work shows that ten naive subjects can be trained in a synchronous paradigm within 3 sessions to navigate freely through a virtual apartment, whereby at every junction the subjects could decide by their own, how they wanted to explore the virtual environment (VE). This virtual apartment was designed similar to a real world application, with a goal-oriented task, a high mental workload and a variable decision period for the subject. All subjects were able to perform long and stable motor imagery over a minimum time of two seconds. Using only 3 electroencephalogram (EEG) channels to analyze these imaginations, we were able to convert them into navigation commands. Additionally, it could be demonstrated that motivation is a very crucial factor in BCI research; motivated subjects perform much better than unmotivated ones.**

***Index Terms*— Brain-Computer Interface (BCI), electroencephalogram (EEG), motor imagery, navigation, virtual reality (VR), virtual environment (VE), neutral cue, motivation**

I. Introduction

VOLUNTARY mental activity (e.g. a sequence of thoughts) modifies bioelectrical brain activity and consequently the electroencephalogram (EEG). A brain-computer interface (BCI) is able to detect such changes in the ongoing EEG and translates different brain states into operative control signals. Therefore, BCI technology can establish a direct communication channel between the human brain and a machine which does not require any motor activity [1], [2].

A BCI-system is, in general, composed of the following components: Signal acquisition, preprocessing, feature extraction, classification (detection), application interface and feedback. It is a closed-loop system with feedback as one important component. Depending on whether the BCI-application is to establish communication in patient with severe motor paralysis, or to control a neuroprosthesis, or to perform neurofeedback, information is visually feed back to the user about success or failure of the intended act. In previous works it could already be demonstrated that virtual reality (VR) can be used as a feedback medium [3] and it is possible to control a virtual environment (VE) with a BCI [4], [5], [6], [7].

The Graz-BCI is based on the analysis and classification of sensorimotor EEG patterns generated during the imagination of specific movements (motor imagery of left and right hand) [8], [9]. EEG-electrodes are placed over the sensorimotor hand and foot representation areas, and the dynamics of sensorimotor rhythms are analyzed in real-time to extract a control signal [10]. Motor imagery can be described as a mental rehearsal of a motor act without any overt motor output [11]. Similar brain regions are activated during motor execution and motor imagery, however, the performance is blocked at some corticospinal level. Functional brain imaging studies showed that changes in the metabolism revealed similar activation patterns during motor imagery and actual movement [12]. Therefore motor imagery has been shown to represent an efficient mental strategy to operate a BCI [2].

The aim of the study is threefold: First, to overcome the limitations of the laboratory conditions towards real world applications, whereby subjects can act goal-orientated with a high cognitive load and without any time constraints to decide whatever and whenever they want. Second, to demonstrate that motivation is a very crucial component in BCI research and influences the classification results. Third, to use long-lasting imagery patterns, instead of single classification points, that can be used by the subjects in the future for brain-switch like applications.

II. Methods

In this section, first the data acquisition of the various biosignals and the applied EEG artifact reduction method are described. Next, the recorded screening data (without feedback) is analyzed to obtain subject specific features which could be used in the following steps to give cue-based feedback. Afterwards the subjects were confronted with a VR feedback and variable trial length, thereby the subjects could decide by their own how they wanted to explore the VE. Finally a cue-based session had been performed.

A. Subjects and data acquisition

Ten naive subjects (6 male and 4 female, age 24.7±3.3 years) participated in this study. The subjects were right handed, had normal or corrected to normal vision and got paid for attending to the experiments. Each volunteer was seated

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in an armchair, fixating on an LCD computer monitor, placed approximately 1 m in front at eye level.

An electrode cap (Easycap, Germany) was fitted to the subject's head, and the EEG electrodes (Ag/AgCl electrodes) were placed according to the extended 10/20-system [13] (see Fig. 1.a). In case of the initial screening twenty-two EEG channels were recorded, but in all feedback sessions the number was reduced to 3 bipolar recordings (C3, Cz and C4). The recordings had a dynamic range of ± 100 μV, were analog band pass filtered (0.5 Hz to 100 Hz) and notch filtered at 50 Hz. In addition to the EEG channels, the electrooculogram (EOG) was recorded with three monopolar electrodes (see Fig. 1.b) using the same settings, but with a dynamic range of ± 1 mV. Four electromyogram (EMG) channels were recorded, whereby the electrodes were placed over the *musculus extensor digitorum* and over the *musculus flexor digitorum superficialis* of the left and the right arm, with reference on the back of the right hand (see Fig. 1.c). The EMG was amplified and integrated over 10 ms with a separated EMG amplifier (Raich, Austria). All biosignals were sampled with a sampling frequency of $f_s = 250\ Hz$.

The recording system consisted of two 16-channel biosignal amplifier (g.tec, Guger Technologies OEG, Graz, Austria), one data acquisition cards (E-Series, National Instruments Corporation, Austin, USA) and a standard personal computer running Windows XP operating system (Microsoft Corporation, Redmond, USA). The recording was handled by rtsBCI [14], based on MATLAB 7.0.4 (MathWorks, Inc., Natick, USA) in combination with Simulink 6.2, Real-Time Workshop 6.2 and the open source package BIOSIG [15].

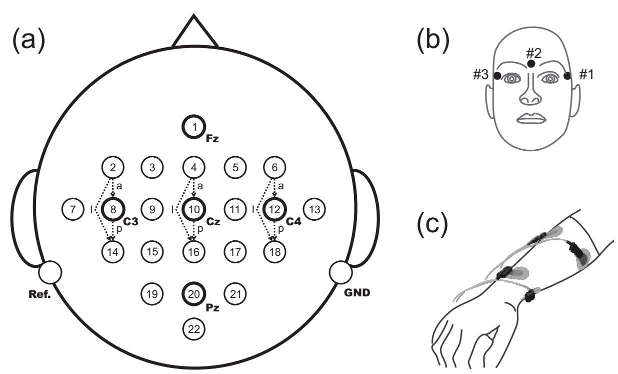

Fig. 1. (a) Placement of the 22 EEG and (b) the 3 EOG electrodes. For both, the reference electrode was placed at the left and the ground electrode at the right mastoid. (c) Location of the EMG electrodes on the right hand placed over the *musculus extensor digitorum* and the *musculus flexor digitorum superficialis*; for the left hand the same positions have been used. The arrows between the EEG electrodes show the analyzed bipolar derivations ($\oplus \rightarrow \ominus$), "a" stands for anterior-central, "p" for central-posterior and "l" for the large distance between the bipolar electrodes (anterior-posterior).

B. Eye movement artifact reduction

At the beginning of each session, a recording of approximately 5 minutes was performed to estimate the EOG influence and to calculate the correction coefficients. The recording was divided into 3 blocks: (i) two minutes with eyes open (looking at a fixation cross on the screen), (ii) one minute with eyes closed and (iii) one minute with eye artifacts. The artifact block was divided in four sections (15 seconds artifacts with 5 seconds resting in between) and the subjects were instructed via written text on the monitor to perform either eye blinking, rolling, up-down or left-right movements. At the beginning and at the end of each task a low and high warning tone, respectively, were presented.

Regression analysis was used to reduced the influence of eye movements on the EEG [16], therefore the block (iii) was used to set-up the correction coefficients. It can be assumed that the recorded EEG S is a superposition of the real EEG signal E and the three spatial EOG components O (horizontal, vertical and radial). In this study, the EOG activity was recorded with three monopolar electrodes (see Fig. 1.b), from which the horizontal and the vertical EOG component can be derived. Accordingly, the corrected EEG E can be computed by subtracting the EOG components $E = S - O \cdot b$. The correction coefficient b is calculated by computing the autocorrelation matrix C_{OO} of the bipolar EOG channels and the cross-correlation C_{SO} between the recorded EEG S and EOG O.

$$b = C_{OO}^{-1} C_{SO} = (O^T O)^{-1} O^T S \qquad (1)$$

The correction coefficients were used in all following experiments on that day to reduce the influence of the EOG artifacts in the EEG recordings.

C. Initial screening, training without feedback

Each naive subject had the task to perform kinesthetic motor imagery (MI) [17] indicated by the visual cue on the monitor (see Fig. 2.a). Prior to the first motor imagery training the subject executed and imagined different movements for each body part and selected the one which they could imagine best (e.g. squeezing a ball or pulling a brake). The cue-based experimental paradigm consisted of two imagery classes: motor imagery of left hand and right hand. Each subject participated in two sessions recorded on two separated days within two weeks. Each session consisted of six runs with ten trials each and two classes of imagery. This resulted in 20 trials per run and 120 trials per session. Data of 120 repetitions of each MI class were available for each person in total. Each trial started with a fixation cross and an additional short acoustic tone (1 kHz, 70 ms). Some seconds later a visual cue (an arrow pointing either to the left or right, according to the requested class) was presented for 1.25 seconds. Afterwards the subjects had to imagine the corresponding hand movement over a period of 4 seconds. Each trial was followed by a short break of at least 1.5 seconds. A randomized time of up to 1 second was added to the break to avoid adaptation (see Fig. 2.a). Twenty-two monopolar EEG channels (reference left mastoid, ground right mastoid) were recorded (see Fig. 1.a).

D. Signal processing: feature extraction and classification

Band power (BP) features were estimated from the ongoing EEG by digitally bandpass filtering the recordings (Butterworth IIR filter of order 5), squaring and averaging the samples over the past second. Finally, the logarithm was computed

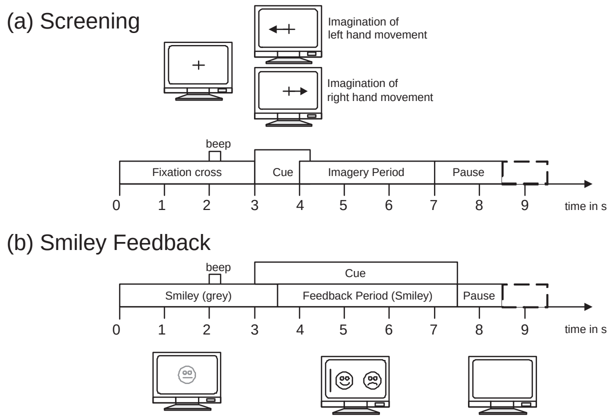

Fig. 2. (a) Timing of the movement imagery task (screening). The cue stimulus between second 3 and 4.25 in form of an arrow (either pointing to the left or right) instructs the participant to imagine the desired movement. (b) Timing of the cue-based feedback experiments and principle of the smiley paradigm.

from this time series. For classification between the two motor imageries, Fisher's linear discriminant analysis (LDA, [18]) was applied to the BP estimates (sample-by-sample). In the Graz-BCI the feature extraction and classification is performed with the sample-rate of the data acquisition (250 Hz). The monitor update rate of the feedback is reduced to 25 Hz.

In contrast to other BCI applications [2], [8], [19], not only the classification error at one specific time point, but the performance over a time interval was investigated. Therefore the LDA output (with < 0 for left class, > 0 for right class) was integrated over the time interval of interest (N samples), resulting in an integrated classification output (iCO). Analogical to the standard classification error based on the LDA output an integrated classification error (iCE) based on the iCO could be calculated. In the presented offline optimization this iCE was calculated over the central most interesting part of the feedback time (from second 4.5 to 6.5, see Fig. 2.a). During the online experiments the iCO was calculated over the past two seconds and used to control the feedback.

E. Subject-specific electrode selection and feature optimization

The philosophy of the Graz-BCI is to use as few as possible electrodes for online experiments, which makes the BCI more comfortable and easier to apply for subjects, and especially for patients. Therefore the precondition was to use only three bilaterally arranged bipolar channels over the sensorimotor areas, corresponding to electrode positions C3, Cz and C4 (according to the 10/20-system), which could be extracted out of the 22 channel screening data (see Fig. 1.a). For each of the three electrode positions (C3, Cz and C4), three different pairs could be generated, two of them with a small distance between the bipolar electrodes (anterior - central, central - posterior) and one with a large distance (anterior - posterior). Therefore nine possible channel combinations were analyzed separately.

For each of the three bipolar channels, BP features in 72 frequency bands were calculated - namely 21 overlapping narrow bands (width 2 Hz, overlap 1 Hz), 19 overlapping bands (width 4 Hz, overlap 1 Hz), 17 overlapping bands (width 6 Hz, overlap 1 Hz) and 15 overlapping broad bands (width 8 Hz, overlap 1 Hz) between 8 and 30 Hz – yielding to a total of 216 different BP features. These features were fed into a feature selection algorithm (sequential floating forward selection, SFFS [20]), which selected at most 6 features out of these 216. The principle of the SFFS is to first search for the most important feature and adds this to the list of selected features. Afterwards the next important feature in combination with the already chosen ones is searched and so one. Early selected features can also be removed from the list, if a combination of later selected features achieves better results. This principle is continued till the maximum number of features is reached. Basically, a feature selection algorithm is an optimization technique that attempts to select a subset of the given features that leads to the maximization of some criterion function. The fitness function used here was the iCE (calculated from second 4.5 to 6.5, see Section II-D). To estimate the separability of the 2-class MI data with the selected BP features the LDA discriminant function was trained with a 10x10 cross-validation. This optimization procedure was performed for each of the nine possible channel combinations and the combination with the best performance was chosen for further feedback experiments.

F. Cue-based feedback training with smiley

For the online feedback experiments, only three bipolar electrode pairs (C3, Cz and C4, based on the results of the offline analysis, see Section II-E) were recorded apart from the EOG and EMG. Electrode position Fz served as EEG ground. After the initial recording and the calculation of the EOG correction coefficients, 4 runs have been performed in each feedback session, whereby each run consisted of twenty trials for each type of motor imagery. As feedback a smiley was used. At the beginning of each trial (second 0) the feedback, a gray-colored smiley, was positioned in the center of the screen (Fig. 2.b). At second 2 a short warning beep (1kHz, 70ms) was given. The cue was presented from second 3 to 7.5. According to the cue, the subjects were given the task to move the smiley towards the left or right side by imagining left or right hand movements, respectively. During the feedback period the smiley changed to the color green when moved in the correct direction, otherwise the color was red. The distance of the smiley from the origin was set according to the integrated classification output over the past two seconds (see Section II-D). Furthermore, it was also mapped to the curvature of the mouth causing the smiley to be happy (corner of the mouth upwards) or sad (corner of the mouth downwards) according to correct classification or misclassification (see Fig. 2.b). At second 7.5 the screen was blanked and a random interval between 1.0 and 2.0 seconds was added to the trial. The subject was instructed to keep the smiley on the correct side for as long as possible and therefore to perform the imagery as long as possible. If the subjects could achieve a stable or continuously improving result with an iCE error of below 25 %, only two cue-based feedback sessions were performed, otherwise an additional session was performed to give the subject an opportunity for further training.

G. Classifier update

After each feedback session, two new classifiers were calculated based on the record ed data. The first classifier used the features (frequency bands) already selected and merely updated the LDA weights. The second classifier was calculated after a new feature selection optimization was performed (see Section II-E). The updated classifier or the optimized classifier, respectively, was only used in the next session if the integrated classification error could have been decreased significantly by 5 %.

H. Exploring Virtual Environments: Desktop-VR "TFT"

The next important step was to use a more flexible paradigm instead of the trial-based analysis (see Section II-F, cues indicating the type of imagination and predefined short analysis windows, e.g. 4-s). In this paradigm, only the start of the decision period was indicated. The subject could decide for himself which motor imagery he wanted to perform and therefore which direction he wanted to select. The duration was variable and depended only how fast or slow the user wanted to perform the decision.

Therefore a virtual apartment (see Fig. 3.a) was modeled and used as virtual reality feedback controlled by the BCI [5], [6]. The subjects were placed in front of a normal TFT monitor and had the opportunity to walk through this virtual apartment. The creation of the 3-D virtual environment consists of two consecutive steps: first the creation of a 3-D model of the scene and second the generation of a VR application which controls and animates the modeled scene. In our experiments, the 3-D modeling software package Maya (Alias, Toronto, Canada) was used for creation and Qt application framework (Trolltech, Oslo, Norway) for the visualization and animation (collision detection). The communication between the BCI and Qt was realized using the User Data Protocol (UDP).

In this virtual apartment, the subject could freely decide where to go, but walking was only possible along predefined pathways through the corridors or rooms. At every junction the subject could decide to go in one of the two directions which were indicated by a "neutral" cue consisting of two arrows (see Fig. 3.c). The subject received feedback by viewing the size of the arrows (update time 40 ms, see Fig. 3.d) which were modulated depending on the BCI classification output (iCO). The analysis was performed till the iCO over the past two seconds was 1 (only one class was detected in this period). In this case, the corresponding arrow was huge and the subject was turned to the right/left/straight. Afterwards the system automatically guided the subject to the next junction. Additionally a small map (bird-view) of the apartment was inserted in the bottom right corner of the display.

As stated above, a "neutral cue" was used to indicate the starting point of the decision period (similar to the cue-based BCI), but the neutral cues were completely embedded in the given task and the duration of the decision periods (similar to trials) was variable, depending only on the performance of the subject. If the subject was able to immediately focus on one thought for at least two seconds, the intended cue was selected, otherwise it could take longer to select a cue and therefore the trial time was very variable.

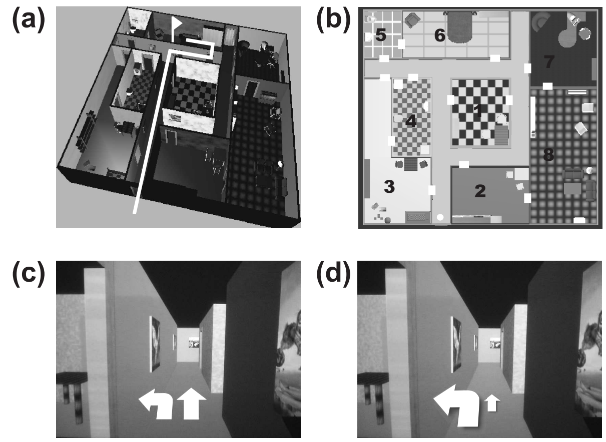

Fig. 3. (a) View into the virtual apartment, with one possible pathway plotted in white. The target room is marked with a small flag pole (in this example, the room at the upper end of the apartment). (b) All possible target rooms have been numbered. The entrance point is marked with a dot and the doors with thick lines. (c) First-person view of the virtual apartment with two arrows indicating the possible directions to go ("neutral cue"). (d) The size of the arrow indicates the BCI classification output.

Each subject performed 12 runs with variable duration in the virtual apartment, but all runs started at the same point (entrance door). During the first run, no instructions were given to the subjects, so they could walk freely through the apartment for 5 minutes to become familiar with the VE. In all other runs the subjects were instructed to go to a predefined target room. A small flag pole on the map indicated the destination, which should be reached by using the shortest way through the maze like apartment (see Fig. 3.a). In the first two runs, only one target was given, but in further runs the number of targets was increased and only one target was visible each time. If this target was reached, either the follow-up target was inserted or the run was finished. Each run was limited to 5 minutes. In the last six runs the subjects had to draw their chosen path on a printout of the apartment before going there. The performance error can be calculated by dividing the number of wrong decisions by the total number of junctions.

I. Exploring Virtual Environments: High-Immersive VE System "iVE"

The same experiment as in Section II-H was carried out in an immersive virtual environment (iVE), whereby the apartment was projected on a single back-projected stereoscopic wall (dimensions 3 * 2.4 m, Barco Galaxy, Barco N.V., Kortrijk, Belgium). The subject had to wear shutter glasses (CrystalEyes, StereoGraphics Corporation, San Rafael, USA) to see the two separate stereoscopic images generated for each eye of the observer. The basic idea is to let the user become immersed in a 3-D scene [21]. The tasks given to the subject were the same as in Section II-H, except that different target rooms had been chosen.

J. Concluding feedback session with smiley

Finally, one cue-based smiley feedback session (same as in Section II-F) was performed with each subject, to see if any influence on the performance after the VR applications could be found.

K. Statistical analysis

Both, the performance error (in %) in the navigation experiments and the integrated classification error (in %) in the cue-based feedback experiments, describe the ability of the subject to keep the correct imagination over a defined period of two seconds. For each subject error from the following sessions has been used in the analysis:

- *scr*: the screening session
- *cb_a* and *cb_b*: the last two cue-based sessions before the virtual feedback (either cb 1 & cb 2 or cb 2 & cb 3, depending on the subject, see Table II)
- *TFT* and *iVE*: the error of the two sessions with virtual feedback
- *cb_c*: the final cue-based session (either cb 5 or cb 6, depending on the subject, see Table II)

As statistical analysis an ANOVA with repeated measurement design was carried out to examine the effect of performance over the sessions (k=6). The results of the Kolmogorov-Smirnov test confirmed, that the error rate (in %) of all measurements is normal distributed (exact p-values between p=0.753 and p=1.000). The Greenhouse-Geisser epsilon correction of degrees of freedom was applied if required. Posthoc paired samples t-tests with a conservative Bonferroni correction were used to isolate significant differences.

III. Results

In the results section, the artifacts (eye movements and EMG) are first analyzed, then afterwards the subject-specific feature selection and the results of the cue-based training are presented. Next, the outcomes of exploring the virtual apartment are described, before the statistical analysis is performed.

A. Eye movement artifact reduction

The EOG regression method eliminates the EOG in the EEG and hence modifies the EEG, therefore the data has been visual inspected twice (before and after regression) by an expert and trials containing artifacts were marked. Without EOG correction, the number of trials containing artifacts was in the range of 20 %, after applying EOG regression nearly all EOG artifacts were removed and the number or trials containing artifacts could be reduced to less than 9 %. These results are in the line with the outcome of Schlögl et al. [16] where this regression method has been proposed.

B. EMG analysis

The maximum amplitude of all recorded four EMG channels during the feedback time for all subjects is between 2.28 and 24.28 μV (mean $\pm$ SD = 9.58 $\pm$ 4.38 μV). Slightly different EMG electrodes placements achieved varying values in some subjects. Nevertheless the activity is much smaller compared to execution of movements. An example of such an EMG recording is given in the upper panel of Fig. 4. The maximum EMG activity occurring during the feedback time is marked with a horizontal line. For comparison reasons, an example of a movement execution, which was recorded only for demonstration purposes, is given in the lower panel of Fig. 4. The amplitude of the EMG recording during the imagination is twenty times smaller than during execution.

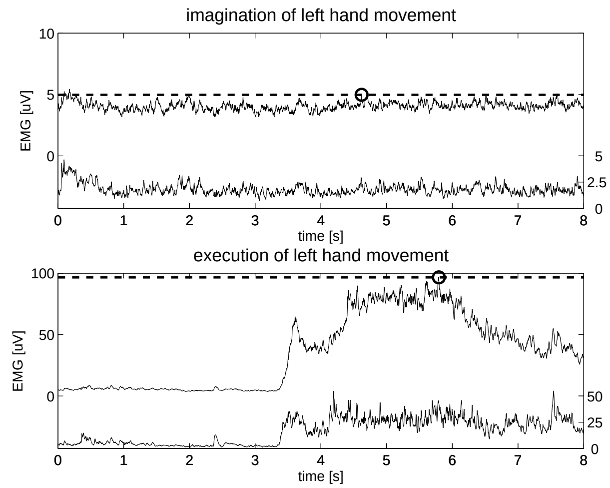

Fig. 4. Example of the EMG recorded over the musculus extensor digitorum of the left hand during the imagination (upper panel) and execution (lower panel) of a left hand movement of one run of subject z22. In each panel the upper curve shows the mean and the lower curve the SD over the trial time (cue at second 3). Please note that the scaling in the imagination panel is only a tenth of the amplitude in the execution panel! The level of the maximum occurring EMG activity during the feedback period is marked with a horizontal dashed line and a circle.

Furthermore, the EMG has been used in an offline simulation to classify the trials. Instead of the six EEG features, the power (averaged over the past second, like the EEG band power) of the four EMG channels (two on the left and two on the right hand) was analyzed. A LDA discriminant function was trained with a 10x10 cross-validation. The resulting classification error for this 2-class problem was 40.85 % $\pm$ 4.11 %. No significant correlation (Pearson's correlation $r = 0.236$) between the EEG classification error and the EMG classification error could be found.

C. Subject-specific electrode and feature selection

The best symmetric electrode location for each subject in terms of the highest classification accuracy is presented in Table I. The most reactive BP features for these electrode locations are given beside them. As mentioned above in Section II-E, the SFFS feature selection algorithm found the best feature subsets consisting of one to six elements. The alpha and upper beta band of electrodes C3 and C4 contributed substantially to classification.

As characteristics of the offline separability of the screening data, the commonly used classification error (err), the time point of the lowest error (t_{err}) and the iCE over the central part of the feedback time from second 4.5 to 6.5 are presented

TABLE I

Results of the optimization for each subject: best electrode locations and corresponding frequency bands are presented ("a" stands for anterior-central, "p" for central-posterior and "l" for large distance between the bipolar electrodes anterior-posterior).

subject ID	electrode location		BP bands
aa8	C3	a	11-13 Hz, 25-27 Hz
	Cz	p	08-10 Hz, 15-21 Hz
	C4	a	11-13 Hz, 21-25 Hz
ac9	C3	l	11-13 Hz, 24-28 Hz
	Cz	l	11-13 Hz, 19-27 Hz
	C4	l	08-12 Hz, 17-19 Hz
ad1	C3	a	15-17 Hz, 18-20 Hz, 24-28 Hz
	Cz	l	18-20 Hz
	C4	a	15-21 Hz, 26-30 Hz
ad2	C3	a	10-12 Hz
	Cz	p	16-20 Hz
	C4	a	08-10 Hz, 10-12 Hz, 13-17 Hz, 19-23 Hz
x20	C3	p	11-13 Hz, 22-30 Hz
	Cz	p	11-13 Hz
	C4	p	09-11 Hz, 11-13 Hz, 24-30 Hz
x21	C3	l	10-12 Hz, 12-14 Hz, 23-27 Hz
	Cz	l	
	C4	l	10-12 Hz, 12-14 Hz, 24-26 Hz
z15	C3	a	13-15 Hz, 15-17 Hz
	Cz	p	
	C4	a	13-15 Hz, 16-18 Hz, 28-30 Hz
z16	C3	a	10-12 Hz, 20-22 Hz, 23-25 Hz
	Cz	p	10-12 Hz
	C4	a	10-12 Hz, 19-23 Hz
z17	C3	l	09-11 Hz, 12-14 Hz, 21-23 Hz
	Cz	l	14-16 Hz
	C4	l	11-13 Hz, 14-16 Hz
z22	C3	a	12-14 Hz, 23-25 Hz
	Cz	p	22-24 Hz, 24-28 Hz
	C4	a	12-14 Hz, 22-26 Hz

TABLE II

Classification error (err), time point of the lowest error (t_{err}), integrate classification error over the feedback time (iCE), time of minimal iCE (t_{iCE}) and classifier change ("-" no change, "o" optimized or "u" updated classifier used) is shown for each subject and session ("scr" indicates screening, "cb" cue based feedback, "tr" training without feedback).

subject ID	session	err [%]	t_{err} [s]	iCE [%]	t_{iCE} [s]	classifier change
aa8	scr	20.1	6.56	25.8	6.56	o
	cb 1	29.8	5.06	35.3	6.18	o
	cb 2	27.9	5.22	35.9	7.10	u
	cb 3	31.6	5.76	34.5	6.35	-
	cb 6	31.9	5.74	35.3	6.35	-
ac9	scr	35.6	6.96	39.3	6.56	o
	cb 1	35.9	6.33	42.3	7.10	u
	cb 2	38.2	7.34	46.5	7.10	-
	cb 3	39.2	5.30	45.1	5.99	-
	cb 6	37.6	5.01	44.3	5.90	-
ad1	scr	30.0	5.32	36.6	6.56	o
	cb 1	37.9	5.76	43.2	6.88	u
	tr	30.6	4.48	38.6	6.44	u
	cb 2	44.3	5.20	49.7	6.69	-
	cb 3	43.7	5.19	47.2	7.10	-
	cb 6	46.6	7.39	51.6	6.10	-
ad2	scr	7.9	5.27	15.5	6.54	o
	cb 1	1.9	5.77	7.5	7.04	u
	cb 2	1.0	5.32	6.6	6.62	-
	cb 5	5.7	5.52	12.8	6.71	-
x20	scr	18.2	5.21	22.6	6.44	o
	cb 1	16.1	6.26	22.4	7.02	-
	cb 2	17.0	5.20	20.4	6.47	-
	cb 5	15.7	5.34	21.8	6.85	-
x21	scr	22.5	6.50	26.7	6.56	o
	cb 1	26.4	5.00	34.3	6.68	u
	cb 2	17.3	5.27	24.7	6.81	-
	cb 5	16.6	5.34	23.6	6.26	-
z15	scr	31.3	6.83	35.8	6.55	o
	cb 1	32.8	6.15	34.5	7.01	o
	cb 2	24.1	6.16	32.7	6.49	u
	cb 3	30.1	5.91	33.7	6.68	-
	cb 6	28.7	6.22	32.8	7.10	-
z16	scr	44.1	4.53	50.4	6.56	o
	tr	14.6	5.53	22.5	6.56	o
	cb 1	12.2	5.74	17.8	7.05	u
	cb 2	11.1	5.36	17.3	6.47	-
	cb 5	6.6	5.31	14.7	6.31	-
z17	scr	31.5	5.22	36.7	6.56	o
z22	scr	26.4	6.02	31.5	6.56	o
	cb 1	20.4	7.50	23.2	7.08	-
	cb 2	16.4	7.50	22.0	6.97	-
	cb 5	19.2	5.75	23.9	6.49	-
mean		25.0	5.84	30.7	6.64	
std		11.7	0.90	11.5	0.32	

in Table II. Various window sizes (1 sec, 1.5 s, 2 s, 2.5 s and 3 s) had been applied for the iCE during the electrode selection and feature optimization process. A length of 2 second was found to be suitable for all subjects.

D. Cue-based feedback training with smiley

Although some subjects did not have a good performance during the screening process, no subject was removed from the study. Unfortunately one subject had no time to continue the feedback training after the first session. Therefore no further data is available for subject z17. The remaining nine subjects performed either two or three cue-based feedback sessions depending on their performance. In Table II the online results (classification error, iCE...) are given. The performance of subject z16 and ad1 was initially so poor, that an additional training run without feedback was performed to help the subject to increase their performance. If necessary, the classifier was updated after each session (see Section II-G). The information concerning which classifier (updated, optimized or old existing one) was selected for the next session is given in the last column of Table II.

The subjects can be ordered according to their performance into four groups: (i) two subjects (ad1 and ac9) performed very poorly, (ii) two subjects (aa8 and z15) performed acceptably, (iii) three subjects (x20, x21, z22) performed well and (iv) two subjects (ad2 and z16) performed excellently. Every subject (except the very poor ones) obtained better results with feedback compared to the screening sessions. All good subjects could improve their performance with the number of cue-based feedback sessions and the poor subjects could achieve stable results. The online performance of one subject is displayed in Fig. 5.

E. Exploring Virtual Environments: Desktop-VR (TFT) and High-Immersive System (iVE)

An example of the planned and the chosen pathway of subject z16 is given in Fig. 6. The first junction was passed

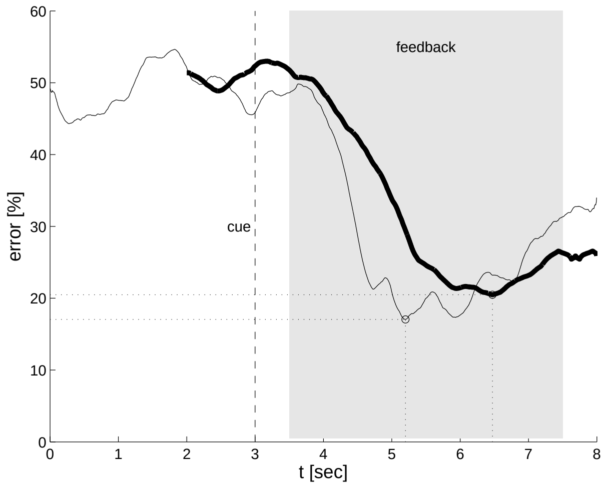

Fig. 5. Online performance of subject x20, session cb 2. The classification error is plotted in thin and the integrated classification error in bold. The cue is indicated with a vertical line and the feedback period with a rectangle. The minimal errors, as given in Table II are marked with circles.

correctly, but at the second junction a mistake occurred, the third and fourth crossings were performed correctly to return to the original path and the subject entered the target room. Therefore one wrong decision and three correct decisions were performed in this run. Dividing the number of wrong decision by the total number of junctions results into the performance error of the VR task (see Table III). Differentially to the previous examples the number of trials/decisions in a run varied depending on the chosen path (between 2 and 38). The mean error rates for all subjects were between 7.0 % and 33.3 %, nevertheless a large number of runs (39) had been performed without a single wrong decision. All subjects (except aa8) improved their performance from TFT to iVE by 3.5 % in mean. Furthermore, the analysis was more demanding, since one wrong decision required several correct decisions to reach the same goal. The time necessary for a decision at the junctions varied for all subjects between 2.06 and 20.54 seconds, with a mean $\pm$ SD of 2.88 ± 0.52 seconds (see last column in Table III).

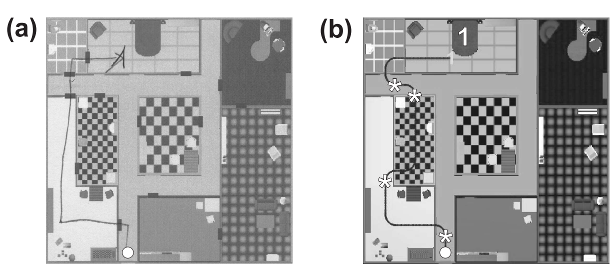

Fig. 6. (a) Scanned drawing of the planned pathway of subject z16. (b) Actual performed pathway. The target room is indicated with the number 1. Crossings are marked with a "*". The entrance point into the apartment is on the bottom of the figure, marked with a dot.

F. Statistical analysis

The summary of all experiments is given in Table IV, therefore the performance error in the navigation experiments

TABLE III

FOR BOTH FEEDBACK CONDITIONS THE NUMBER OF WRONG DECISIONS AND THE NUMBER OF JUNCTIONS ARE GIVEN. THE PERCENTAGE OF WRONG DECISIONS (THE ERROR) AND THE TIME NECESSARY FOR THE DECISIONS ARE CALCULATED.

subject ID	VR session	wrong decisions	total decisions	performance error [%]	decision duration $\pm$ SD [s]
aa8	TFT	39	222	17.6	2.82 ± 0.39
	iVE	59	226	26.1	2.81 ± 0.44
ac9	TFT	80	264	30.3	2.88 ± 0.45
	iVE	68	248	27.4	2.84 ± 0.38
ad1	TFT	89	267	33.3	2.81 ± 0.38
	iVE	93	282	33.0	2.96 ± 1.61
ad2	TFT	13	154	8.4	2.87 ± 0.33
	iVE	9	128	7.0	2.66 ± 0.20
x20	TFT	38	148	25.7	2.78 ± 0.29
	iVE	24	169	14.2	2.86 ± 0.42
x21	TFT	51	207	24.6	3.17 ± 0.73
	iVE	52	215	24.2	2.94 ± 0.57
z15	TFT	89	239	37.2	2.81 ± 0.33
	iVE	59	238	24.8	3.09 ± 0.63
z16	TFT	37	152	24.3	2.79 ± 0.28
	iVE	27	144	18.7	3.05 ± 1.26
z22	TFT	52	218	23.9	2.89 ± 0.38
	iVE	30	168	17.9	2.84 ± 0.35
mean		50.5	204.9	23.3 ± 8.1	2.88 ± 0.52

(see Table III) and the integrated classification error in smiley feedback experiments (see Table II) have been combined. The performed ANOVA with repeated measures revealed a significant difference in the error (%) over the sessions (F1.657,13.253=4.183; p=0.045). Post hoc t-tests for paired samples showed significant differences between the screening session (scr) and the sessions with virtual reality feedback (TFT: t(8)=2.308; p=0.050 and iVE: t(8)=3.247; p=0.012). Additionally, significant differences between the iVE session and the first (cb_a: t(8)=3.883; p=0.005) as well as the second cue-based session (cb_b: t(8)=2.950; p=0.018) could be detected. A significant difference was also found between the final cue-based session cb_c and the iVE session (t(8)=-3.114; p=0.014). No significant difference could be found between the final cue-based session (cb_c) and the last cue-based session (cb_b) before the virtual feedback (t(8)=-1.098; p=0.304). Interestingly, no significant difference between the two virtual feedback session (TFT and iVE) could be detected (t(8)=1.680; p=0.131), but 8 of 9 subjects performed better in the iVE condition. In Fig. 7 the mean and standard error over all subjects is given and the statistical differences between the sessions are marked.

IV. DISCUSSION

Online EOG regression and the analysis of the recorded EMG showed that only brain activity was used for control. Notwithstanding, the adaptation of subject-specific features and electrode position is crucial to obtain reliable performances, particularly if only a small number of electrodes should be used. As expected from literature [22] oscillations in the alpha and beta range of the EEG over the sensorimotor areas contribute substantially to the discrimination between different MI.

The subjects noted that the task in the virtual apartment was much harder compared to the prior feedback training,

TABLE IV

INTEGRATED CLASSIFICATION ERROR AND PERFORMANCE ERROR IN PERCENT OF ALL SUBJECTS. THE DATA HAVE BEEN REARRANGED, WHEREBY CB_A AND CB_B CORRESPOND TO THE LAST TWO CUE-BASED SESSIONS BEFORE THE VIRTUAL FEEDBACK (EITHER CB 1 & CB 2 OR CB 2 & CB 3 DEPENDING ON THE SUBJECT, SEE TABLE II) AND CB_C TO THE FINAL CUE-BASED SESSION (SEE TABLE II). THE VALUES FOR TFT AND IVE HAVE BEEN COPIED FROM TABLE III.

subject	scr	cb_a	cb_b	TFT	iVE	cb_c
aa8	25.8	35.9	34.5	17.6	26.1	35.3
ac9	39.3	46.5	45.1	30.3	27.4	44.3
ad1	36.6	49.7	47.2	33.3	33.0	51.6
ad2	15.5	7.5	6.6	8.4	7.0	12.8
x20	22.6	22.4	20.4	25.7	14.2	21.8
x21	26.7	34.3	24.7	24.6	24.2	23.6
z15	35.8	32.7	33.7	37.2	24.8	32.8
z16	50.4	17.8	17.3	24.3	18.7	14.7
z22	31.5	23.2	22	23.9	17.9	23.9
mean	31.6	30.0	27.9	25.0	21.5	29.0
SE	3.4	4.5	4.4	2.8	2.6	4.4

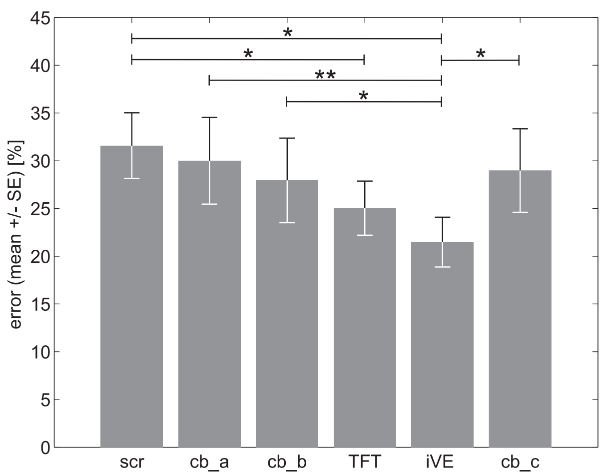

Fig. 7. Mean $\pm$ standard error (SE) over all subjects of the integrated classification error and performance error, respectively. The asterisk (* $p \leq 0.05$; ** $p \leq 0.01$) shows statistically significant post-hoc differences.

because it was necessary not only to perform the "correct" imagination, but also the shortest way through the apartment had to be found. Therefore the cognitive load was much higher compared to the standard BCI paradigm. According to our hypothesis, we found that the performance improves (decrease of error) over the sessions and the lowest error could be found during the sessions with virtual feedback. The slight but stable performance improvement of all subjects is very well known as the training effect [2], [8]. Subjects reported a motivational effect when switching from standard cue-based feedback to virtual feedback, which is clearly visible in the results. The first VR feedback session (TFT) was new, unknown and exciting for the subjects, therefore especially in the good subjects a slight drop in their performance could be found. Contrary to that, the poor subjects improved more significantly, because they vanquished their frustration over their bad performance and focused harder on the given task. These findings are in line with the reports of the subjects given after the experiments. In the second VR session (iVE) the subjects adapted to the higher mental load and performed best compared to all other sessions (see Table III and Fig.7). The return from the virtual feedback to the standard cue-based feedback removed all the motivation and the performance of all subjects dropped. The lowest error occurred in the sessions with the virtual feedback. This cannot be explained by the training effect, because that would mean the last session should have the lowest error, which is not the case. This effect could best be explained by the increased motivation. These findings are in line with the outcomes of fMRI experiments, which showed that motivation/mental effort during a motor imagery task can enhance the BOLD signal [23].

All subjects were able to deal with the variable trial length (the duration of the trial depended on how fast or slow the subject could perform a decision) and the variable inter-trial interval. The flexible length permitted the subject to correct indistinct initial thoughts and to "struggle" for the desired result, which is not possible in common synchronous BCI's. The time necessary for a decision in the sessions with the virtual apartment (2.88 seconds) was very similar to the sessions with cue-based feedback (subtracting the 3.5 seconds before the feedback time from time of minimal iCE (t_{iCE}) of 6.64, leaded to 3.14 seconds).

In these experiments it was planned to go one step away from the laboratory conditions towards real world applications. In the real world, all our activity is goal-orientated, and the time necessary for our decision depends only on what we want and how we want to achieve it, therefore the introduction of this maze-like apartment with neutral cues, variable trial lengths and with the cognitive load of finding the shortest way, was a very promising example of a possible real world application, which is still analyzable in terms of BCI performance.

Using long-lasting and stable imagery patterns, instead of single classification points, allows a very robust identification without influences or disturbances. Therefore the subjects (especially patients) have the possibility to use their brain signals for suitable control tasks outside the laboratory conditions. It is disadvantageous that the information transfer rate (which is the commonly used BCI measurement for success [2], [19], [24], [25]) is decreased, but in reality the signal is much more usable for the subjects —which is the most important goal. Additionally, these long-lasting signals can be better distinguished from the non-control state [26] and can be used in the future for brain-switch like communication applications, especially in the area of rehabilitation engineering [27].

V. CONCLUSION

The research reported is a further step away from laboratory conditions towards real world applications. The naive subjects first trained in a synchronized environment and afterwards used their trained imagination patterns in an environment with neutral cues and unassigned decision periods. This study showed that with three bipolar electrodes it is possible for BCI novices after a few training runs to successfully navigate through a virtual apartment using only their imagination of movements. The subjects choose freely the way to reach their goal. So each subject had his own strategy. Nevertheless, the identified brain activities could be used for control applications even in situations with a high cognitive load. In a further step it is planned to use an asynchronous implementation of such a virtual navigation task [28]. Additionally, it could be proved that motivation is a very crucial factor in BCI research. Motivated subjects perform much better than subjects who are bored of their task. Good subjects always perform very well, but especially bad subjects can increase their performance significantly. This is very important during the BCI training process.

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