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Abstract

Healthy participants are able to move forward within a virtual environment (VE) by the imagination of foot movement. This is achieved by using a brain-computer interface (BCI) that transforms thought-modulated electroencephalogram (EEG) recordings into a control signal. A BCI establishes a communication channel between the human brain and the computer. The basic principle of the Graz-BCI is the detection and classification of motor-imagery-related EEG patterns, whereby the dynamics of sensorimotor rhythms are analyzed. A BCI is a closed-loop system and information is visually fed back to the user about the success or failure of an intended movement imagination. Feedback can be realized in different ways, from a simple moving bar graph to navigation in VEs.

The goals of this work are twofold: first, to show the influence of different feedback types on the same task, and second, to demonstrate that it is possible to move through a VE (e.g., a virtual street) without any muscular activity, using only the imagination of foot movement. In the presented work, data from BCI feedback displayed on a conventional monitor are compared with data from BCI feedback in VE experiments with a head-mounted display (HMD) and in a high immersive projection environment (Cave). Results of three participants are reported to demonstrate the proof-of-concept. The data indicate that the type of feedback has an influence on the task performance, but not on the BCI classification accuracy. The participants achieved their best performances viewing feedback in the Cave. Furthermore the VE feedback provided motivation for the subjects.

I Introduction

“Yes he was walking! The illusion was utterly convincing” experienced the leading character from Arthur C. Clark’s book *3001, The Final Odyssey* (1997), when he was wearing a “Braincap” connected to the “Brainbox.” Thereby he could experience this science fiction technology and explore different virtual and ancient real worlds. Has this dream become real? This question was addressed by the presented work which shows that participants are able to move forward—to walk—within a VE by imagining movements of their foot.

The improvement of seamlessness and naturalness of human-computer in-

terfaces is a necessary task in virtual reality (VR) development. One interesting research problem is to realize locomotion through a VE using mental activity or thoughts. Generally, participants navigate in VEs by using a hand-held device, such as a joystick or a wand. This could present the user with contradictory stimuli. On the one hand the world around them is moving, which generates the illusion of walking, but on the other hand the participant is thinking about his action to press the button on the joystick. This results in a reduced sense of being present in the VE (Slater, Usoh, & Steed, 1995), and can cause simulation sickness (Hettinger & Riccio, 1992).

A possible step towards next-generation interfaces could be achieved by exploiting a BCI which represents a direct connection between the human brain and the computer (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). The electroencephalogram (EEG) of the human brain contains different types of oscillatory activities. The oscillations in the alpha and beta band (event-related desynchronization, ERD; Pfurtscheller & Neuper, 2001) are particularly important to use in discriminating between different brain states (e.g., imagination of movements). A BCI transforms thought-modulated EEG signals into control commands (Wolpaw et al., 2002). Classical applications of BCI include the restoration of communication for individuals who have lost the ability to communicate by speech or other muscular activities (i.e., patients in a “locked-in state”) and the control of a neuroprosthesis in patients with a spinal cord injury (Pfurtscheller & Neuper, 2001; Wolpaw et al., 2002).

Recently, the BCI has been used to control events within a VE, but most of the previously conducted VR-BCI research is based on two types of visually evoked responses; either the steady-state visual evoked potential (SSVEP; Lalor et al., 2005; Middendorf, McMillan, Calhoun, & Jones, 2000) or the event-related P300 potential (Bayliss, 2003). These methods typically force the subjects to perform a visual task that might be unnatural (e.g., to gaze at a blinking object). In contrast, our research uses a different BCI paradigm for VR control based on motor imagery (Leeb, Scherer, Keinrath,

Guger, & Pfurtscheller, 2005; Pfurtscheller & Neuper, 2001).

The goals of this work are twofold: first, to demonstrate that it is possible to move through VEs (e.g., a virtual street) without any muscular activity, using only the imagination of foot movement recorded with a BCI; and second, to show the influences of different feedback types on the same task.

VR provides an excellent testing ground for procedures that may someday be used in the real world. In the future VEs could be an important tool for people with disabilities. If it is possible to show that people are able to control their movements through space within a VE, it would justify the much bigger expense of building physical devices like a robot arm controlled by a BCI. Bayliss (2003), for example, enumerates the general advantages of VR for BCI as follows: “it is a safe environment, it can be used to control the experience and reduce distractions, and it can be highly motivating.” Further applications include the use of VR as a feedback medium with the goal of enhancing the classification accuracy and reducing the time needed for BCI training sessions. This feedback medium could be used for improving the rehabilitation of stroke victims by using virtual body parts as feedback and for motor rehabilitation of patients with brain injuries or Parkinson’s disease (Holden, 2005).

2 Background

Direct brain-computer communication is an approach to develop an additional communication channel for human-machine interaction. In this case, the normal communication channels such as speech and movement are not used, but instead the brain activity is directly recorded and transformed into a control signal. Therefore, a BCI provides a new communication channel that can be used to convey messages and commands directly from the brain to the external world. During the operation of the BCI, the user’s task is to intentionally “produce” certain brain states (i.e., EEG patterns) that can be detected by the system. This can either be achieved by self-regulation of the relevant EEG features (Bir-

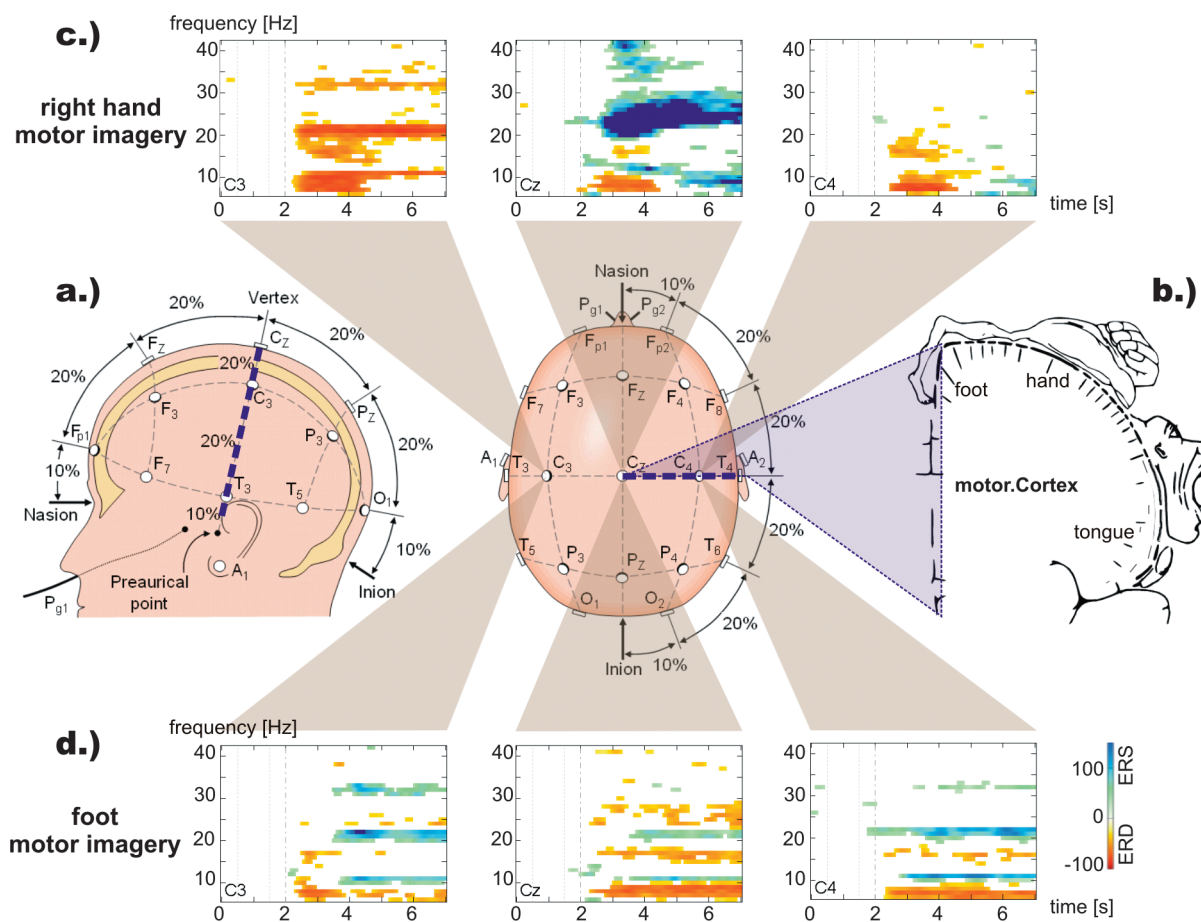


Figure 1. (a) EEG-electrode positions of the international 10/20 system in side view and top view. In the presented experiments only the positions C3, Cz, and C4 have been used. (b) Sensorimotor representation of body parts on the cerebral cortex. (c) Time frequency maps (ERD/ERS-Maps) of the electrodes C3, Cz, and C4 during right hand motor imagery and during (d) foot motor imagery. Event-related desynchronization (ERD) is plotted in red and event-related synchronization (ERS) in blue. The data used for these maps are marked with asterisks in Figure 5, later in the paper.

baumer et al., 2000) or by using a specific mental strategy, for example, the mental imagery of movements (Wolpaw et al., 2002).

2.1 Neurophysiological Background

Populations of neurons can form complex networks in which feedback loops are responsible for the generation of oscillatory activity. In general, the frequency of such oscillations becomes slower with increasing numbers of synchronized neuronal assemblies. Two types of oscillations have importance for the EEG-based

BCI: the Rolandic mu rhythm in the range of 7–13 Hz and the central beta rhythm above 13 Hz, both originating in the sensorimotor cortex (see Figure 1b). Sensory stimulation, motor behavior, and mental imagery can change the functional connectivity within the cortex and result in an amplitude suppression (event-related desynchronization, ERD) or in an amplitude enhancement (event-related synchronization, ERS) of mu and central beta rhythms (Pfurtscheller & Lopes da Silva, 1999). The dynamics of brain oscillations associated with sensory and cognitive processing and motor behavior can form complex spatiotemporal patterns. For ex-

ample, a synchronization of higher frequency components embedded in a desynchronization of lower frequency components can be found on a specific electrode location at the same moment of time. Simultaneous desynchronization and synchronization of 10 Hz components are possible on different scalp locations. Preparation and planning of self-paced hand movement results in a short-term desynchronization (ERD) of Rolandic mu and central beta rhythms. The general finding is that similar to the mu rhythm (around 10 Hz), beta oscillations desynchronize during the preparation and execution of a motor task. However, alpha and beta frequency components differ with respect to temporal behavior.

2.2 Motor Imagery

Motor imagery is described as the mental rehearsal of a motor act without any overt motor output (Decety, 1996). It is broadly accepted that mental imagination of movements involves similar brain regions that are used in programming and preparing such movements (Jeannerod & Frak, 1999). According to this view, the main difference between motor performance and motor imagery is that in the latter case execution would be blocked at some corticospinal level. Indeed functional brain imaging studies monitoring changes in the metabolism revealed similar activation patterns during motor imagery and actual movement performance (Lotze et al., 1999). Motor imagery, defined as mental simulation of a movement, has been shown to represent an efficient mental strategy to operate a BCI (Pfurtscheller, Neuper, & Birbaumer, 2005). The imagination of different types of movements, for example, right hand, left hand, foot, or tongue movement, results in a characteristic change of the EEG over the sensorimotor cortex of a participant (Pfurtscheller & Neuper, 2001).

As an example for the dynamics of brain oscillations, time-frequency maps (ERD/ERS maps; Graimann, Huggins, Levine, & Pfurtscheller, 2002) of right hand and foot motor imagery are presented in Figures 1c and 1d. The imagination of a right hand movement results in a desynchronization of mu (8–12 Hz) and central beta rhythms (13–28 Hz) over electrode C3 and in an

enhanced 24 Hz component at channel Cz. The red color in each map marks a significant power (amplitude) decrease or ERD and the blue color a significant power (amplitude) increase or ERS of the corresponding frequency component. During the imagination of foot movement the 10 Hz, 20 Hz, and 30 Hz components were enlarged (characteristic of the arch-shaped mu rhythm). In summary, it can be stated that foot motor imagery synchronized and induced brain oscillations in the hand representation area (channels C3 and C4) and hand motor imagery in the foot representation area (channel Cz).

2.3 Basic Principle and Components of a Brain-Computer Interface

A BCI system is, in general, composed of the following components: signal acquisition, preprocessing, feature extraction, classification (detection), and application interface (Figure 2). The signal acquisition component is responsible for recording the electrophysiological signals and providing the input to the BCI. Preprocessing includes artifact reduction (electrooculogram, EOG, and electromyogram, EMG), application of signal processing methods, that is, low-pass or high-pass filter, methods to remove the influence of the line frequency and in the case of multichannel data the use of spatial filters (bipolar, Laplacian, common average reference). After preprocessing, the signal is subjected to the feature extraction algorithm. The goal of this component is to find a suitable representation (signal features) of the electrophysiological data that simplifies the subsequent classification or detection of specific brain patterns. There are a variety of feature extraction methods used in BCI systems. A less than exhaustive list of these methods includes amplitude measures, band power, Hjorth parameters, autoregressive parameters, and wavelets. The task of the classifier component is to use the signal features provided by the feature extractor to assign the recorded samples of the signal to a category of brain patterns. In the simplest form, detection of a single brain pattern is sufficient. This can be achieved by using a threshold method. More sophisticated classifications of different patterns depend on lin-

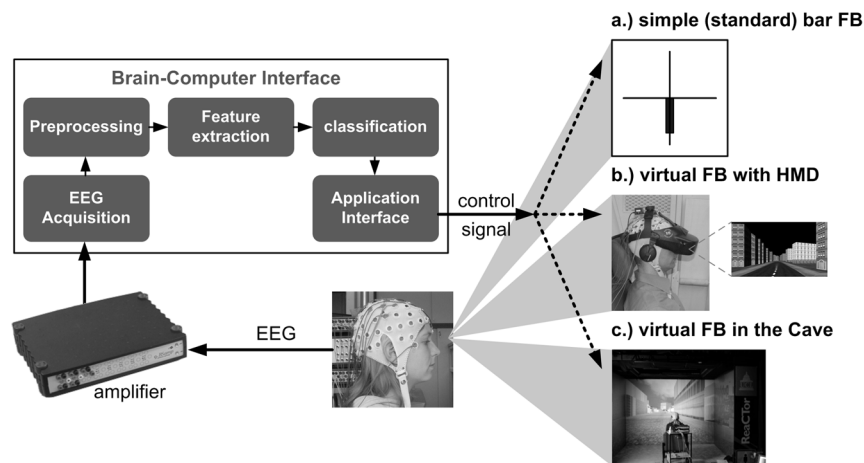


Figure 2. Schematic model of the used BCI-VR system with the participant wearing the electrode cap. Three different visual feedback modalities are displayed: (a) standard feedback whereby a vertical bar is controlled by the BCI output. (b) The participant is wearing an HMD. A screenshot of the virtual environment as seen by the participant is displayed at the far right. (c) Picture of one participant during the experiment in a Cave-like system. The surrounded projected environment creates the illusion of being in a virtual street. (b, c) Navigation through the VE is controlled by the output of the BCI.

ear or nonlinear classifiers (Pfurtscheller & Neuper, 2001). The classifier output, which can be a simple on-off signal or a signal that encodes a number of different classes, is transformed into an appropriate signal that can then be used to control a VR system.

Further information about the physiological background of motor imagery and ERD (Pfurtscheller & Lopes da Silva, 1999; Pfurtscheller & Neuper, 2001), about signal processing, feature extraction and the Graz-BCI (Guger et al., 2001; Pfurtscheller, Neuper, et al., 2003), and generally about various BCI systems (Vaughan et al., 2003; Wolpaw et al., 2002) can be found elsewhere.

3 Methods

3.1 Graz Brain-Computer Interface

The Graz-BCI detects changes in the ongoing EEG during the imagination of hand or foot movements and transforms them into a control signal (Pfurtscheller et al., 2003). Three EEG-electrode pairs

were placed 2.5 cm anterior and posterior to positions C3, Cz, and C4 of the international 10/20 system (Jasper, 1958; see Figure 1a). The EEG was recorded with a sampling frequency of 250 Hz (sensitivity was set to 50 μ V) and bandpass filtered between 0.5 and 30 Hz. The ground electrode was positioned on the forehead (position Fz).

The logarithmic bandpower (BP) was calculated for each of the three channels by digitally bandpass filtering the EEG (using a Butterworth filter of order 5) in the upper alpha and beta band (using subject-specific frequency bands), squaring and log-transforming the signal, and averaging the samples over a 1-s epoch. The resulting 6 BP features were transformed with Fisher's linear discriminant analysis (LDA; Bishop, 1995) into a single control signal. Finally, the computed control signal was used to control/modify the feedback (FB). It was either visualized on the same PC as a bar graph (see Figure 2a) or sent to the VE as a locomotion input inside a virtual world (see Figures 2b and 2c; Leeb et al., 2005).

The experimental paradigm in the Graz-BCI can be divided into the following steps:

1. Training without feedback to acquire subject specific data for the used imaginations.
2. Setup of the classifier based on the data of step 1. If the classification accuracy is above 70%, move on to the next step, otherwise continue with step 1.
3. Training with feedback (online processing of EEG signals).
4. Search for optimal frequency bands.
5. Classifier update, if the frequency bands have been modified or the EEG patterns have been changed.
6. Application to virtual reality.

In general, multichannel recordings using various mental strategies could be performed in the beginning. Furthermore offline optimization could be applied to determine the best mental strategies, electrode positions, and frequency bands. In the experiments reported, the mental strategies and the electrode positions were fixed.

A BCI with feedback consists of two adapting systems, the computer (classifier) and the human subject (brain); see Figure 3. The so called man-machine learning dilemma (MMLD) implies that two systems (man and machine) are strongly interdependent but have to be adapted independently (Pfurtscheller & Neuper, 2001). The starting point of this adaptation is the training of a machine to recognize certain EEG patterns of a man. During this phase, no feedback is given. As soon as feedback is provided, each cycle results in an adaptation of man to machine: man tries to repeat success and avoid failure. Wrong feedback can elicit frustration, a response likely to be associated with a widespread EEG desynchronization (unspecific activation), whereas a correct feedback reinforces the desired EEG patterns (specific and localized activation). In both cases, the feedback could introduce noise and deteriorate the classification performance. Therefore the machine (in our case the classifier) is not updated after every run or session as long as the performance of the subject was similar to the previous sessions and as long as the newly calculated classifier would not dramatically increase the performance (improvement > 5%). If the subjects are

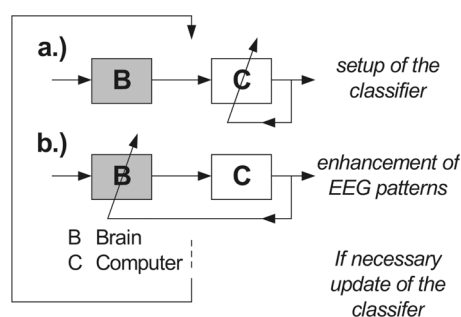


Figure 3. A BCI consists of two adapting systems, the computer (C) and the human brain (B). Both systems are strongly linked, but can only be adapted independently.

well trained (classification accuracies above 90%) they can produce the same EEG patterns over a long period (many years; Pfurtscheller, Guger, Müller, Krausz, & Neuper, 2000; Pfurtscheller, Müller, Pfurtscheller, Gerner, & Rupp, 2003).

The complete biosignal analysis system used consisted of an EEG amplifier (g.tec, Graz, Austria), a data acquisition card (National Instruments Corporation, Austin, USA) and a recording device running under WindowsXP (Microsoft Corporation, Redmond, USA) on a commercial desktop PC (Guger et al., 2001). The BCI algorithms were implemented in MATLAB 6.5 and Simulink 5.0 (The MathWorks, Inc., Natick, USA) using rtsBCI (Scherer, 2004–2006) and the open source package BIOSIG (Schlögl, 2003–2006).

3.2 Participants and Experimental Paradigm

Three healthy participants (between 23 and 30 years old) took part in these experiments over 5 months. All were right handed, without a history of neurological disease, had normal or corrected to normal vision, and were paid for participating in the study. The subjects were familiar with the Graz-BCI (over a period of between four month and two years), but had no prior experience with VR (neither HMD nor Cave).

The performances of three different FB conditions are compared: first the results of the standard BCI bar-FB with a simple bar (see Figure 2a), secondly using an

HMD as the FB device (see Figure 2b), and finally using a highly immersive Cave projection environment (see Figure 2c). Each FB condition was measured multiple times and the order of conditions was bar, HMD, Cave, HMD, bar. Figure 5, to be discussed fully below, displays which type of FB has been used in each run and session, respectively.

In general all daily runs defined one session (between 3 and 8 runs). In each run the subject had to imagine foot or right hand movement in response to an auditory cue stimulus in form of a single beep (hand imagery) or double beep (foot imagery). Each run consisted of 40 trials (20 foot cues and 20 right hand cues) and the sequence of the cues was randomized within each run. The timing of the experiment was based on the standard Graz-BCI paradigm (Pfurtscheller, Neuper, et al., 2003). Each trial lasted about 8 s with a randomized interval in the range of 0.5 to 2 s between the trials. Therefore, a run lasted approximately 6.5 min and one session lasted about an hour, including the time for electrode mounting.

The EEG trials from the first two runs of the first session without FB (marked with TR in Figure 5, discussed fully later) were used to set up an LDA classifier able to discriminate between the two different mental states and the accuracy rates were estimated by a 10 times 10-fold cross-validation LDA-training. For this initial classifier standard frequency bands have been used (10–12 Hz and 16–20 Hz). In further runs, visual FB was given to inform the participant about the accuracy of the classification during each imagery task. After the first two sessions a new classifier based on these data was computed. For the determination of the best frequency bands, the data of the runs with PC-FB (of both sessions) were used in an optimization process based on a genetic algorithm (GA; Goldberg, 1989; Scherer, Müller, Neuper, Graimann, & Pfurtscheller, 2004). The purpose of the optimization task was to find two BP features for each channel, with two nonoverlapping frequency bands best suitable to discriminate between both mental tasks. The optimized frequency bands were for participant P1 11–16 Hz and 22–26 Hz, for participant P2 10–15 Hz and 20–27 Hz, and for participant P3 10–16 Hz and 19–27 Hz. For these optimized frequency bands a new

classifier was calculated and used in all the remaining sessions, independent of the conditions. Further details of BCI training with motor imagery can be found elsewhere (Pfurtscheller, Neuper, et al., 2003).

3.3 Simple Standard BCI Feedback (bar)

In each run the participant had to imagine foot or right hand movement in response to a visual cue stimulus presented on a computer monitor, in the form of an arrow pointing downwards or to the right, respectively. In addition to the visual cue, an auditory cue stimulus was also given either as a single beep (hand imagery) or as double beep (foot imagery). Visual feedback indicated by a moving bar (see Figure 2a) was displayed between 4.25 and 8 s to inform the participant about the accuracy of the classification during each imagery task (i.e., classification of right hand imagery was represented by the bar moving to the right, classification of foot movement imagery made the bar move downward) (Pfurtscheller, Neuper, et al., 2003). The length of the bar was controlled by the LDA-classification output, which corresponded to the distance to the decision hyperplane. A long bar informed the participant that the classifier could identify the EEG patterns very well and a short bar indicated that the identification was weaker.

3.4 Virtual Feedback with an HMD

Virtual reality FB was presented with VRjuggler (VRjuggler, 2005) and a Virtual Research V8 HMD (Virtual Research Systems, Inc., Aptos, USA) driven by an ATI Radeon 9700 graphics card (ATI Technologies, Inc., Markham, Canada). The task of the participant was to walk to the end of the street inside the virtual city, whereby any time the computer identified the participant's brain pattern as a foot movement a motion occurred (see Figure 2b). The same BCI paradigm as in the above described condition (Section 3.3) was used, with the difference that the cue was given only acoustically. Correct classification of foot motor imagery was accompanied by moving forward with constant speed (1.3 length units/s) in the projected virtual street and

Table 1. *Dependency Between the Predetermined Cue Classes and the Movements Imagined by the Subject and Their Resulting Motions Performed in the Virtual Street*

Cue class	Subject imagined	
	Foot movement	Hand movement
Foot movement	Forward	Stop
Hand movement	Backward	Stop

the motion was stopped on correct classification of hand motor imagery (see Table 1). Incorrect classification of foot motor imagery resulted in halting as well, and incorrect classification of hand motor imagery resulted in backward motion (Leeb & Pfurtscheller, 2004). Only during the feedback time of the trial motions could occur and the feedback was updated 20 times per second. The walking distance was scored as a cumulative achieved mileage (CAM), which is the integrated forward/backward distance covered during foot movement imagination and was used as a performance measurement (see Figure 7 later in this paper). Correct classification during the whole feedback time of one trial resulted in a motion of 5 length units and correct classification during the whole run in a maximum motion of 100 lengths units.

3.5 Virtual Feedback in the Cave

Two sessions were performed in London in a multiprojection based stereo and head-tracked VE system commonly known as a Cave (Cruz-Neira, Sandin, & DeFanti, 1993). The particular VE system used was a ReaCTor (SEOS Ltd., West Sussex, UK) which surrounds the user with three back-projected active stereo screens (three walls) and a front projected screen on the floor (see Figure 2c). Left- and right-eye images are alternately displayed at 45 Hz each, and synchronized with CrystalEye stereo glasses. A special feature of any multiwall VE system is that the images on the adjacent walls are seamlessly joined together, so that participants do not see the physical corners but see the continuous

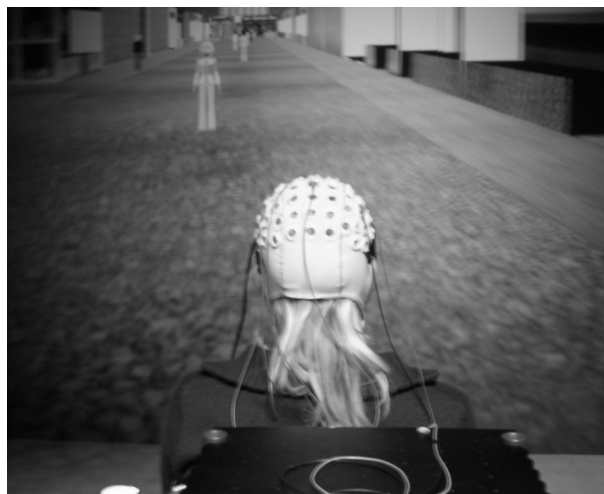


Figure 4. *Participant in the virtual main street with shops and animated avatars during the Cave-FB. The subject wears an electrode cap (connected to the amplifier) and shutter glasses.*

virtual world that is projected with active stereo (Slater, Steed, & Chrysanthou, 2002). The application implemented in DIVE (Frecon, Smith, Steed, Stenius, & Stahl, 2001) was a virtual main street with shops on both sides (see Figure 4). The street was populated with virtual characters who walked along the street and were programmed to avoid collisions with the participant. The task was to go straight forward as far as possible. Communication between the BCI and the VR occurred via the virtual reality peripheral network (VRPN, 2005).

The two street scenes (in the HMD and Cave conditions) were slightly different; the first one was a street through a typical neighborhood with large building blocks on both sides and the second one was a high street with shops and avatars (compare the pictures in Figures 2b and 4). Nevertheless in both conditions the subject was placed in the middle of the street and the task was to walk (as far as possible) to the end of the street. The same BCI paradigm, mapping of motions, feedback update rate, and speed of walking was applied.

4 Results

All participants were able to navigate in the different VE conditions and the achieved BCI performance in

the VR tasks was comparable to standard BCI recordings. The usage of VR as FB stimulated the participant's performance and provided motivation. Especially in the Cave condition (highest immersion) the performance of two participants was excellent (up to 100% BCI classification accuracy of single trials), although variability in the classification results between individual runs occurred (see Figures 5 and 9, covered later in this paper).

In Figure 5 all performed runs over a period of five months with simple standard bar-FB, HMD-FB, and Cave-FB and the training runs without FB (TR) are indicated in each subject. All runs following the indicated date are performed at on that day and are called one session. Concerning the difference between the various feedback modalities, no statistical evaluation of the data was possible, because only three individuals participated in these experiments. Nevertheless, the proof-of-concept could be demonstrated. Two different questions were investigated: one, the influence of the different FBs on the BCI classification accuracy, and two, the locomotion task performance.

4.1 BCI Classification

The BCI classification accuracy is a parameter, indicating how well the two brain states could be identified in each run. A classification accuracy of 100% denotes a perfect separation between the two mental tasks (right hand movement imagination and foot movement imagination). A random classification would result in an expected classification accuracy of 50%. The accuracy varies over the 8 s of each trial (see Figure 6; the example runs are indicated in Figure 5 with a black diamond). At second 3, the participant received an acoustical cue (single or double beep) and started to imagine the indicated movement. The time of optimal classification performance varies between measurements and between individuals (see Figure 6), but it was typically at least 2 s after the trigger (Krausz, Scherer, Korisek, & Pfurtscheller, 2003). Participant P3 achieved an especially long and stable brain pattern over nearly the whole FB time (last row in Figure 6), which directly corresponds to very high CAM in Figure 7, discussed in the next section.

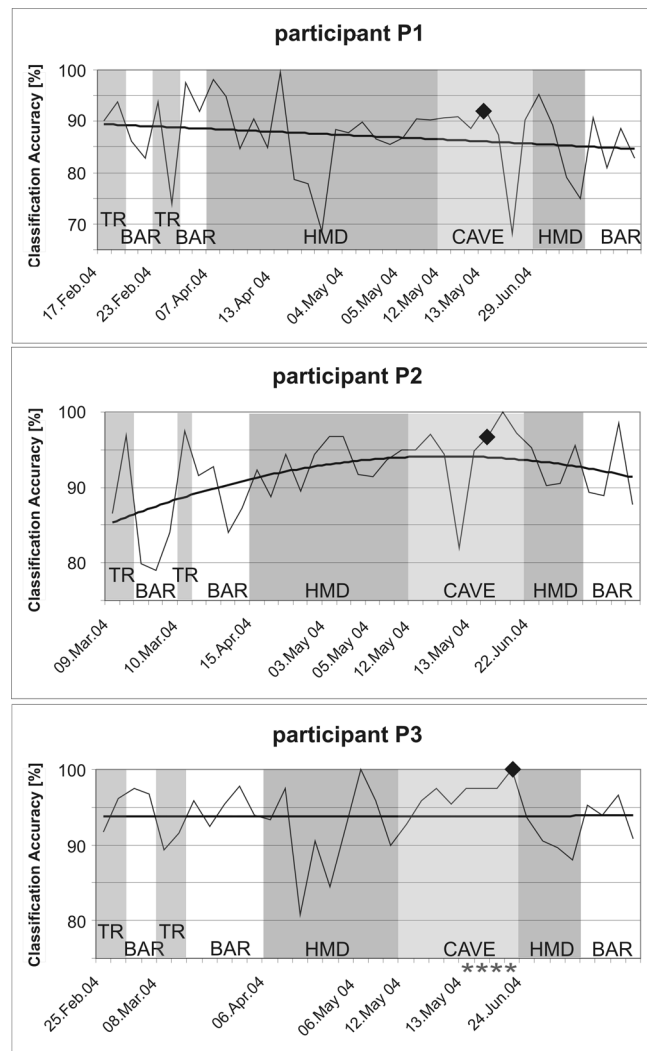


Figure 5. Classification accuracy (in percent) for all runs of the three participants. Runs with bar-FB, HMD-FB, and Cave-FB and the training runs without FB (TR) are indicated in each subject. A second order interpolation shows the trend of the classification accuracy over the time (black line). More than one run has been performed on each day. Therefore, all data points following the indicated date are performed at this day and are called a session. The runs marked with a black diamond ♦ (one in each subject) are analyzed in detail in Figure 6 (classification accuracy) and in Figure 7 (CAM, task performance). The runs marked with an asterisk are used for the ERD/ERS maps in Figure 1.

The results of all runs with FB over a period of five months are displayed in Figure 5. The runs with bar-FB, HMD-FB, and Cave-FB are separately indicated. A sec-

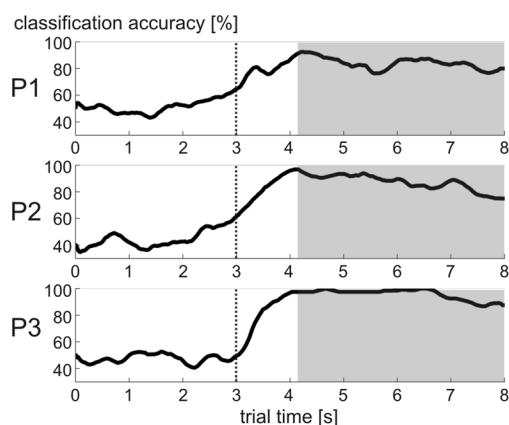


Figure 6. Mean classification accuracy (in percent) of one run (marked with a black diamond in Figure 5) over the trial time of all three participants. At second 3 the participant heard the cue (single or double beep) and started to imagine the specified movement during the FB period (between second 4.25 and 8).

ond order interpolation has been performed to show the trend of the classification accuracy over time (thick black line). The time courses of the classification accuracy for each participant fluctuate considerably over runs. Additionally, different trends are visible in the three participants: in participant P1 the classification accuracy shows a slightly decreasing trend over runs, in participant P2 a maximum during the Cave experiments, and in participant P3 a relatively constant level. In Table 2 the mean and standard deviation (SD) of the classification accuracy with bar-FB, HMD-FB, and Cave-FB are given for each participant. No differences in the mean BCI classification accuracy between the various conditions could be found in participant P1. Participant P2 achieved enhanced accuracies in both VE conditions. In contrast, participant P3 had a slightly decreased accuracy in the HMD condition, with an increased SD. Overall, no influence of the FB condition on the classification accuracy could be found, because the variability was too high in all conditions and subjects.

4.2 Task Performance

The participants were able to achieve a grand average CAM of 49.2%. Single results of the first session

with the Cave-FB obtained for the three participants are displayed in Figure 7 (the runs are indicated in Figure 5 with a black diamond and are the same as displayed in Figure 6). The theoretically possible CAM is plotted in a dashed line and the achieved CAM as a solid line. Because each participant had a different sequence of the 20 foot (F) and 20 right hand (R) motor imageries which were randomly distributed to avoid adaptation, the theoretical pathways are different in all runs. Nevertheless the numbers of trials for both classes are the same and therefore the maximum possible CAM is the same. Participant P3 achieved the best performance with a CAM of 85.4%. A CAM of 100% corresponds to a correct classification of all 40 imagery tasks over the entire feedback time. A random classification would result in an expected CAM of 0%, because 50% of the trials with foot motor imagery would be classified correctly (forward movement) and 50% of the trials with hand motor imagery would be classified wrongly (backward movement). Therefore forward and backward movements would compensate for each other and would result in a CAM of 0%. For comparison reasons the CAM performances of the bar-FB experiments have been simulated offline, because during this type of FB the subject didn't walk, and therefore no CAM was available.

In Figure 8 the mean achieved CAM of all participants and conditions is plotted. The trend of each participant over the FB conditions is plotted as a gray dashed line. Figure 9 displays a detailed analysis of the same data. Each box plot has lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of the box to show the extent of the rest of the performances. The trend of each participant over the three FB conditions is indicated with a gray dashed line. Two participants show an increase over the condition, but participant P1 achieved worse results with the HMD.

It is nearly impossible to achieve the maximum attainable CAM, because every small procrastination or hesitation of the participant results in reduced mileage. For a perfect outcome, a correct classification must occur during the whole FB time of all trials. Therefore the results are not directly comparable to normal BCI classi-

Table 2. Mean \pm SD of the BCI Classification Accuracy in Percentage of All Three Participants and All Three Conditions (bar, HMD, Cave)

FB conditions	Participants		
	P1 (%)	P2 (%)	P3 (%)
bar	87.7 \pm 6.6	88.8 \pm 6.1	94.3 \pm 2.6
HMD	86.8 \pm 7.7	93.1 \pm 2.6	91.3 \pm 5.2
Cave	86.9 \pm 8.4	94.7 \pm 5.4	96.8 \pm 2.1

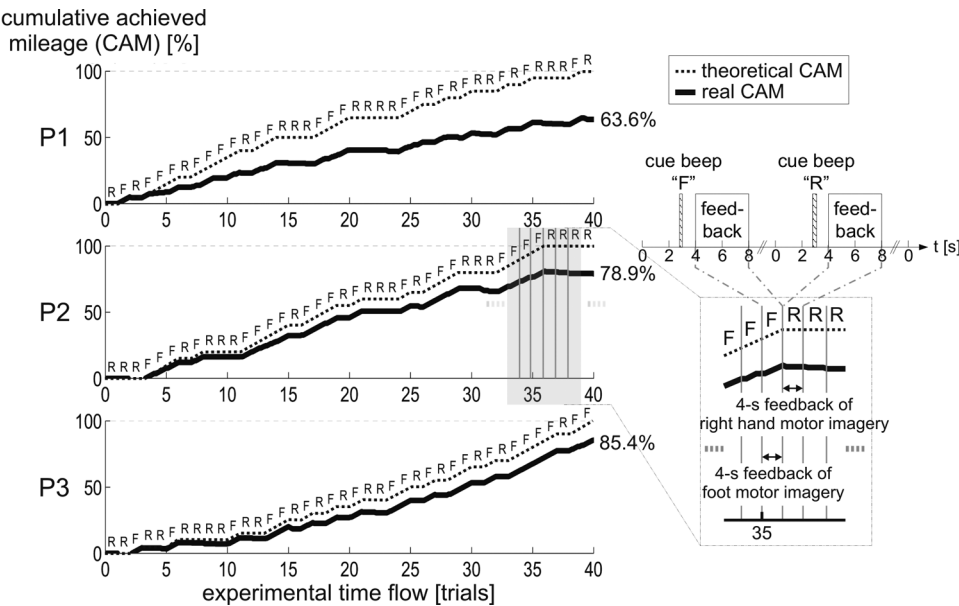


Figure 7. Task performance measures of all three participants (P1, P2, and P3) displayed in the theoretical possibility CAM (dashed line) and the real CAM (full line). The “cumulative achieved mileage” (CAM) is the summed up distance which was walked forward during foot movement imagination. Each subject had a different sequence of the 20 foot (F) and 20 right hand (R) motor imageries, therefore the theoretical pathways are different in all pictures. On the right side of the diagrams the real achieved CAM is written for each subject, with 63.6% for subject P1, 78.9% for P2 and 85.4% for P3. The small picture in the bottom right corner shows a zoomed version of the performance measurements. The F and R sections correspond to the 4 s feedback time during each trial. The cued-paradigm of the BCI has a trial length of 8 s, as can be seen in the timing diagram in the upper right corner. The trigger cue is at second 3 and feedback is given between seconds 4 and 8. Between the trials there is random pause interval.

fication performance results, where only the value of a single time point counts. Because a BCI classification of 100% corresponds to a perfect separation between the

two mental tasks at a time point, but a CAM of 100% corresponds to a BCI classification of 100% over the whole FB time.

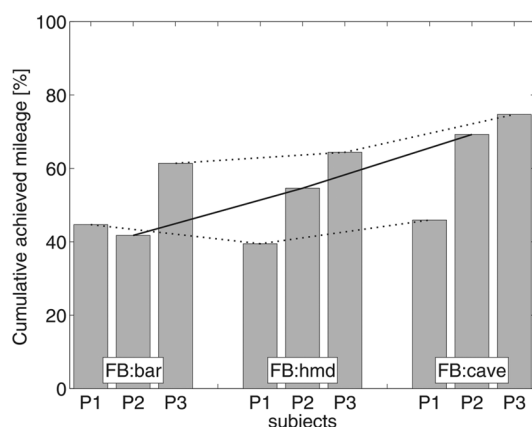


Figure 8. Mean CAM values of all participants and all three FB conditions. The trend of each participant over the FB conditions is plotted as a gray dashed line.

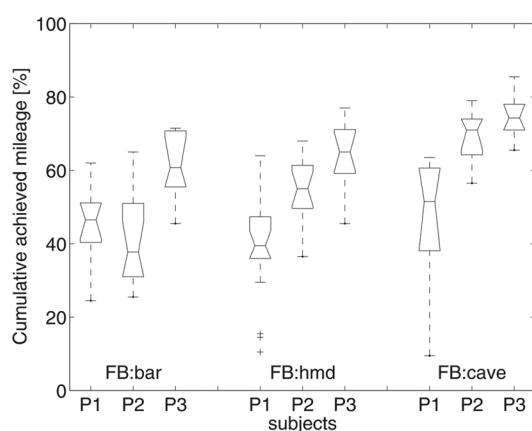


Figure 9. Distribution of the achieved CAM of all participants and all three FB conditions. Each plot has lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of the box to show the extent of the rest of the data.

4.3 BCI, Presence and Body Representation

After completing the experiments in the Cave, the participants were asked to fill in the Slater-Usuh-Steed presence questionnaire (Slater, 1999) followed by an unstructured interview. The results of the questionnaire and interview data have been evaluated separately (Friedman et al., 2004). After the standard BCI experi-

ments and after the HMD experiments no presence questionnaires and interviews were conducted. However, subjects reported that the BCI may be considered as a very unusual extension of the body and since the BCI control became more automatic, they gradually became more absorbed in the VR and felt more present. One subject stated: “it was more like in a dream—you move but you do not feel your body physically move. And just like in a dream—at that moment it seems real.”

5 Discussion and Conclusion

The data indicate that EEG recording and real-time single trial processing is possible with an HMD or in a Cave-like system, and furthermore foot motor imagery is an adequate mental strategy to control locomotion or other events within VEs. Imagination of foot movement is a mental task very close to natural walking. Relatively good performances are obtained with the virtual FBs (Cave better than HMD), excepting some outliers. One reason for some inferior classification results of individual runs, especially in the Cave condition (see Figure 9; e.g., CAM of 9.5% in participant P3) could be the loss of concentration in association with a moving visual scene. This might be due to the fact that perception of moving objects can have an impact on neurons in the motor area (Rizzolatti, Fogassi, & Gallese, 2001). Another possible explanation for the poor results of participant P1 (upper diagram in Figure 7) could be that the participant was asked to imagine the “standing class” (right hand movement) for several trials (trials 14 to 17 and trials 20 to 25) and wasn’t able to remain stationary for such a long period. A similar effect can be observed at the end of the run displayed in the middle diagram of Figure 7. A faster alternation between the two classes might achieve better results, but the sequence of cues was randomized automatically for each run. This long standing period leads to the problem that the feedback doesn’t change over a long time, which again leads to the subjective feeling of receiving no feedback about the actual performance. Because of this it is not intentional on the participant’s part that thoughts are drifting away and maybe the wrong move-

ment is imagined (foot movement) which leads to walking backwards. In that case the subject immediately realizes that his or her thoughts drifted away and focuses again on the desired motor imagery. It could also be observed that walking backwards happened mostly in short and single steps, compared to long-lasting periods of walking forward within a trial.

The data indicate that the type of feedback has an influence on task performance (see Figures 8 and 9), but not on the BCI classification accuracy (see Figure 5 and Table 2). The participants achieved their best task performances during Cave-FB. The argument that only the task experience triggered this result can be disproved, because the conditions were recorded in a different sequence. Furthermore the classification accuracy decreased in participant P1 over time (see Figure 6), which would be contradictory to that argument. Further research is necessary to address the question of whether a VE or an immersive VE as feedback has an impact on the performance or can even shorten the training time. All subjects reported that the Cave sessions were more comfortable than the HMD and both were preferred over BCI training on a monitor.

In principle it should be possible to achieve the same performance in both VE conditions, the HMD and Cave. Participants reported that the limited field of view (FOV) of the HMD and the weight on the head were irritating and bothersome. Also the optical resolution of the HMD was less than in the Cave. The Cave was compared to the HMD as a VE-FB that was much more natural and hence preferable.

The main reason why VR was preferred is that it provided motivation. During the Cave condition the street was treated as a sort of racecourse and each subject wanted to get further than the previous subjects. The motivation seemed to greatly improve BCI performance, with the drawback that too much excitement might have a negative impact, as it makes it harder to concentrate on BCI control. Two subjects had sometimes nearly perfect runs until the last two or three trials of the run. At that time they already realized that they could achieve a new distance record, but this excitement reduced their concentration and therefore the last trials were performed badly. This reduced task performance in

such a way that no new record could be achieved. The aspects of motivation and mental effort during the experiment have a great influence on the BCI performance and must be taken into consideration in all further BCI experiments.

The next important step in this research is a change in the experimental paradigm and to eliminate cue stimuli. In this way the participant could decide to start walking at will. Such an asynchronous or uncued BCI system, however, is more demanding and more complex than BCIs operating with cue stimuli and a fixed timing scheme (Borisoff, Mason, Bashashati, & Birch, 2004; Scherer et al., 2004). In the case of an asynchronous BCI, not only the discrimination between the different motor imagery tasks (control states) is necessary, but also the noncontrol state (resting or idling state) has to be detected correctly. It can be expected that such an asynchronous BCI control would facilitate the sense of presence.

The research reported in this paper is a further step to the long-range vision for multisensory environments exploiting only mental activity. EEG-based BCI systems have a bad signal-to-noise ratio and display a drop of classification accuracy when more than two or three mental states have to be classified (Pfurtscheller et al., 2005; Scherer et al., 2004; Wolpaw et al., 2002). A possible solution was discussed by Nicoletis (2001). He suggested using direct implants into the brain for computer control by directly analyzing the activity of single neurons. Such brain implants (e.g., the Utah array, Maynard, Nordhausen, & Normann, 1997) are already temporarily in use in totally paralyzed patients (Donoghue, 2002; Friebs, Zerris, Ojakangas, Fellows, & Donoghue, 2004) and commercial products are in clinical trials at the moment (e.g., Cyberkinetics Neurotechnology System Inc., Foxborough, USA). In this case the signal-to-noise ratio is excellent and more than two mental states can be classified with high accuracy. Therefore in a long range vision it is possible that such implants will be used in healthy subjects as well. In this way the vision of the science fiction authors using the brain as the ultimate interface will become reality sometime in the future.

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