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Brain-Computer Interface Systems used for Virtual Reality Control

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1. Introduction

A Brain-Computer Interface (BCI) is a non-muscular communication channel for connecting the brain to a computer or another device. Currently, non-invasive BCIs transform thought-related changes in the electroencephalogram (EEG) online and in real time into control signals. In such an EEG-based BCI, specific features are extracted from brain-signals, transformed into a control signal, and used to restore communication to patients with locked-in-syndrome or to control neuroprosthesis in patients with spinal cord injuries (Birbaumer et al., 1999; Pfurtscheller et al., 2008b; Wolpaw et al., 2002). In addition to these applications, which focus on communication and control, the related field of neurofeedback supports feedback training in people suffering from epilepsy, autism, stroke, and emotional or attentional disorders (Birbaumer & Cohen, 2007).
Today the world of BCI applications is expanding and new fields are opening. One new direction involves BCIs to control virtual reality (VR), including BCIs for games, or using VR as a powerful feedback medium to reduce the need for BCI training (Leeb et al., 2007b; Scherer et al., 2008). Virtual environments (VE) can provide an excellent testing ground for procedures that could be adapted to real world scenarios, especially for patients with disabilities. If people can learn to control their movements or perform specific tasks in a VE, this could justify the much greater expense of building physical devices such as a wheelchair or robot arm that is controlled by a BCI. BCIs are more and more moving out of the laboratory and becoming also useful for healthy users in certain situations (Nijholt et al., 2008).
One of the first efforts to combine VR and BCI technologies was Bayliss and Ballard (2000) and Bayliss (2003). They introduced a VR smart home in which users could control different appliances using a P300-based BCI. Pineda et al. (2003) showed that immersive feedback based on a computer game can help people learn to control a BCI based on imagined movement more quickly than mundane feedback, a finding we later validated with other immersive feedback (Leeb et al., 2006; 2007b). Lalor et al. (2005) used a steady-state visual evoked potential (SSVEP)-based BCI to control a character in an immersive 3-D gaming environment. Recently, Leeb et al. (2007b) have reported on exploring a smart virtual

apartment using a motor imagery-based BCI, and Holzner et al. (2009) in an experiment for P300-based BCI for smart home control.
This short overview about BCI applications in VR shows that there are many different types of BCIs. The next section provides a short introduction to BCIs.

2. Definition and basic principles of a BCI

Wolpaw et al. (2002) defined a BCI as a "...new non-muscular channel for sending messages and commands to the external world". Here, we clarify this definition to emphasize that any BCI must have the 4 following components (Pfurtscheller et al., 2010a):

1. Direct recording: The BCI must rely at least partly on direct measures of brain activity, such as through electrical potentials, magnetic fields, or hemodynamic changes.
2. Real time processing: The signal processing must occur online and yield a communication or control signal.
3. Feedback: Goal-directed feedback, about the success or failure of the control, must be provided to the user.
4. Intentional control: The user must perform an intentional, goal-directed mental action to control, such as imagining movement or focusing on a stimulus.

These definitions implicate that each BCI is a closed-loop system with two adaptive controllers: the user's brain, which produces the signals and provides the input to the BCI; and the BCI itself, which analyses the brain signals and transforms them to a control signal as the BCI output (Figure 1).
The EEG is the most widely used brain signal in BCIs (Mason et al., 2007), and is also the most common signal when using a BCI system for VR control. Two types of changes can be extracted from the ongoing EEG signals: one change is time and phase-locked (evoked) to an externally or internally-paced event, the other is non-phase-locked (induced). Evoked signals include event-related potentials (ERPs), including the P300 and SSVEPs (Allison et al., 2008). Induced signals include the dynamic amplitude changes of oscillations in different frequency bands (Pfurtscheller & Lopes da Silva, 1999; Pfurtscheller & Neuper, 2010). Thus, we can differentiate between 2 types of BCI systems. One is based on predefined mental

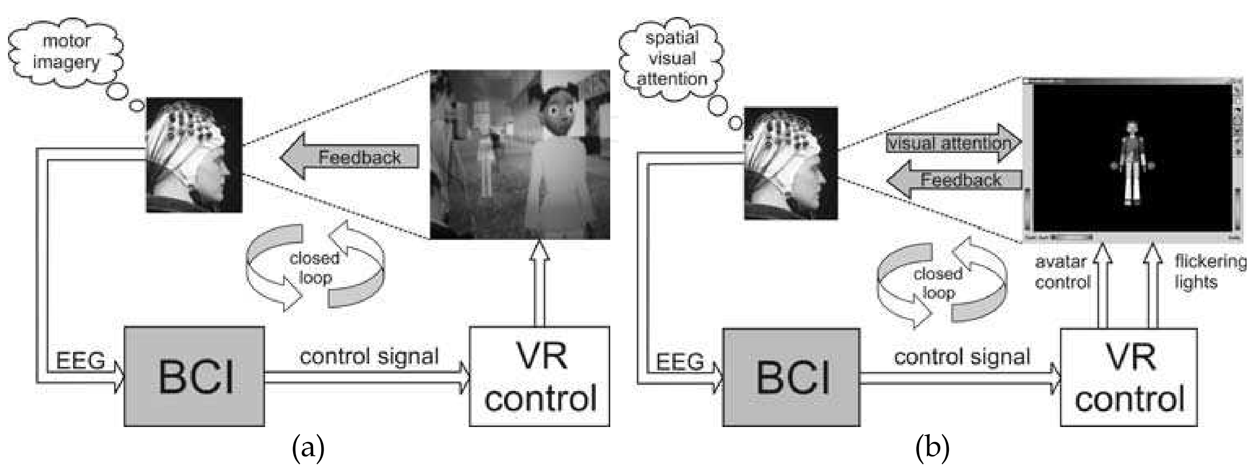


Fig. 1. Principles of BCI systems without (a) and with external stimulation (b). Motor imagery is the most common mental strategy in BCIs which do not rely on external stimulation to generate the necessary brain activity. BCIs that do rely on external stimulation to elicit brain activity typically involve spatial visual attention.

tasks and classifying induced brain activities (Figure 1a), while the other is based on sensory stimulation (e.g. visual) and classifying evoked potential changes (Figure 1b).

Three different BCI approaches have received the most attention in recent years:

P300-based BCI (P300 BCI): The P300 is the positive component of the evoked potential that may develop about 300 ms after an item is flashed. The user focuses on one flashing item while ignoring other stimuli. Whenever the target stimulus flashes, it yields a larger P300 than the other possible choices. P300 BCIs are typically used to spell (Allison & Pineda, 2006; Donchin et al., 2000; Farwell & Donchin, 1988), but have been validated with other tasks such as control of a mobile robot (Bell et al., 2008) or a smart home control (Holzner et al., 2009).

SSVEP-based BCI (SSVEP BCI): Steady-state evoked potentials (SSEPs) occur when sensory stimuli are repetitively delivered rapidly enough that the relevant neuronal structures do not return to their resting states. In a BCI application, the user focuses on one of several stimuli, each of which flicker at a different rate and/or phase. Flickering light sources are typically used to trigger steady-state visual evoked potentials. Gao et al. (2003) described a BCI with 48 flickering lights and a high information transfer rate of 68 bits/min. This was the fastest BCI reported in the published literature until recently, when the same group described some improved approaches (Bin et al., 2009). Like P300 BCIs, SSVEP BCIs require no training and can facilitate rapid communication (Allison et al., 2008; Krusienski et al., 2006). SSVEP BCIs have also recently expanded to tasks beyond spelling, such as controlling a virtual character (avatar) in a computer game (Faller et al., 2010; Lalor et al., 2005; Martinez et al., 2007) or controlling an orthosis (Pfurtscheller et al., 2010b).

ERD-based BCI (ERD BCI, SMR BCI): Brain rhythms can either display an event-related amplitude decrease or desynchronization (ERD) or an event-related amplitude increase or synchronization (ERS) (Pfurtscheller & Lopes da Silva, 1999). The term ERD BCI describes any BCI system that relies on the detection of amplitude changes in sensorimotor rhythms (mu and central beta rhythms) and/or other brain oscillations, also including short-lasting post-imagery beta bursts (beta ERS, beta rebound) (Blankertz et al., 2007; Pfurtscheller et al., 2006a; 2008b; Pfurtscheller & Solis- Escalante, 2009). The term SMR BCI is frequently used when only sensorimotor rhythms are classified (Birbaumer & Cohen, 2007). In the standard protocol, the user performs a motor imagery task to consciously modify brain rhythms. Motor imagery results in a somatotopically organised activation pattern, similar to that observed when the same movement is really executed (Lotze et al., 1999; Pfurtscheller & Neuper, 2010). In particular, hand and feet motor imagery affect sensorimotor EEG rhythms in ways that allow a BCI to detect such changes online and generate a reliable control signal.

The ERD BCI can operate in two different modes: the input data are either processed in a predefined time windows of a few seconds each following cue stimuli (synchronous or cue-based BCI), or continuously sample-by-sample (asynchronous or self-paced BCI). In a synchronous protocol, the user performs a mental task after each cue; the EEG processing is time-locked to externally-paced cues that are repeated in intervals of several seconds because the onset of motor imagery is precisely known. No cue is presented in the asynchronous mode. Hence, the system is continuously available for control, allowing users to freely decide when they wish to generate a control signal. The output (control) signal of a BCI can be either the result of the user's intended control (IC) or intended non-control (INC). In the latter case, during the resting state, undefined mental tasks (thoughts) or artifacts may be erroneously classified as control signals. Such an asynchronous BCI is more complex and demanding for developers, even though it may be easier for the user.

However, asynchronous BCIs have been validated even in advanced situations, such as navigating in a virtual environment (Leeb et al., 2007a; 2007d; Scherer et al., 2008).

3. Virtual Reality system

In order to carry out the VE experiments, two different and complex systems had to be integrated: the BCI and the VR system. Figure 2 shows that both systems run on two different machines (hardware) and different platforms (software). The interaction between them is realized via a network connection (usually TCP/IP).
The participant is placed in the middle of a multi-projection based stereo and head-tracked VR system commonly known as a "CAVE" (Cruz-Neira et al., 1993). The surround projection system consists of three rear-projected active stereo screens (left, right and front wall on which the images are projected from outside) and a front-projected screen on the floor (image for the floor is projected from above), as shown in the right part of Figure 2. It generates three-dimensional stereoscopic representations of computer animated worlds, depending on the current viewing position and direction of the visitor.
The projections on the screens are continuously adapted to the movements of the visitor by re-computing the projected images for the respective current viewing position and direction (update rate of 30 – 50 times per second). The position of the subject is determined using four infrared cameras that keep track of a number of highly retro-reflective balls that are attached to the shutter glasses. This makes it possible to compute images for every screen that accurately fit the visitor's view on the simulated scene.
A special feature of any multi-wall VR system is that the images on the adjacent walls are seamlessly joined together, so that participants do not see the physical corners but the continuous virtual world that is projected with active stereo (Slater et al., 2002). The basic idea is to let a user become immersed in a 3-D scene (Slater & Usoh, 1993). Therefore, the subject has 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 creation of the 3-D virtual environment entails two consecutive steps: first, the creation of a 3-D model of the scene; and second, the generation of a VR-application that controls and animates the modeled scene.

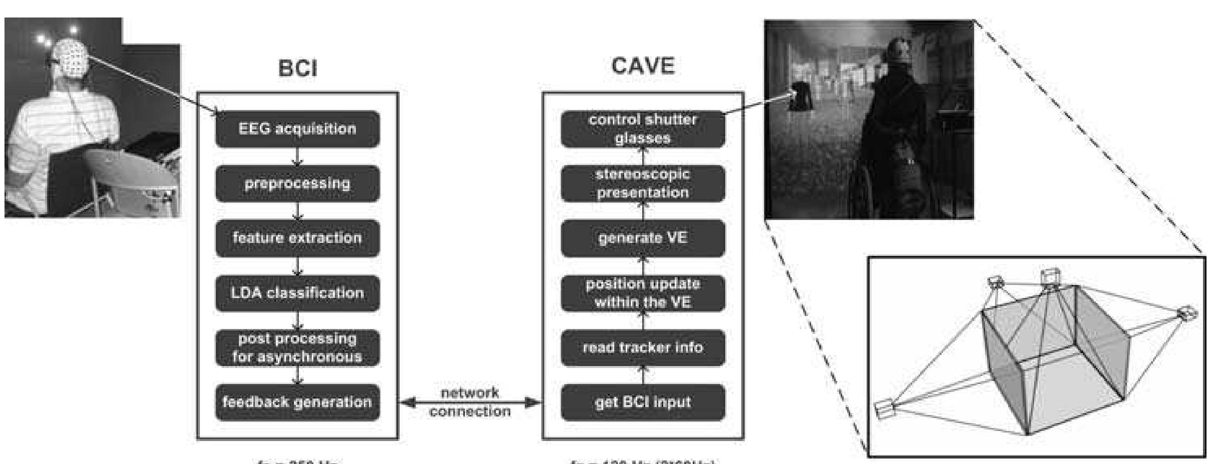


Fig. 2. System diagram of the hardware setup. The BCI system on the left analyses the EEG signals, and the extracted control commands are transferred into movements with the VE projected in the CAVE system. On the right bottom side is the physical CAVE installation with indicated projection screens. Modified from Leeb (2008).

4. Setup of an EEG-based BCI

The first step is always the same. The computer (classifier) has to learn how subject-specific EEG data (trials) look during execution of a predefined mental task. In general, each trial starts with a warning stimulus followed by a cue stimulus, indicating the type of mental task. The task depends on whether the BCI requires external stimulation to generate the necessary brain signals. P300 BCI and SSVEP BCIs do require such stimuli, while ERD BCIs do not. In the former BCI approaches, the user typically must pay attention to one out of 2 or more flickering lights or to flashing letters, numbers, and/or other symbols or commands. In the latter case the user has to perform a motor imagery task (e.g. hand or foot movement imagery) as indicated by the cue stimulus. During this training, about 80 trials of EEG data (each lasting several seconds) are recorded without any feedback to the user and used to set up the classifier. In a second step, the user has to perform the cue-paced mental task, and real-time feedback informs the user about success or failure of the online classification. P300-based and SSVEP-based BCIs have an apparent advantage in that both require no or only minimal user training. In contrast, ERD-based BCIs often need extensive user training, sometimes lasting many weeks (for details see Pfurtscheller et al., 2000; 2006a).
The experimental procedure commonly used with ERD-based BCI research can be divided into the following steps:

1. The (new, naive) subject must be instructed on what exactly is going to be done. It is crucial that the subject performs kinesthetic motor imagery (Neuper et al., 2005).
2. Training without feedback is done to acquire subject specific data for the imagery task used.
3. The most discriminative features (e. g., frequency bands) are extracted from this data.
4. The classifier is set up based on the features from step 3. If the classification accuracy is above 70 %, move on the next step, otherwise continue with step 2. This involves the selection of the best mental strategy, the localization of the best electrode recording sites and the optimal frequency bands.
5. Training with feedback; that is, online processing of EEG signals.
6. Classifier update, if the frequency bands have been modified or the EEG patterns have been changed.
7. Online applications like virtual environments can be controlled.

In general, multi-EEG channel recordings using various mental strategies can be performed at the beginning of step 2. Furthermore, offline optimization can be applied to determine the best mental strategies, electrode positions and frequency bands.
A BCI-system is, in general, composed of the following components: Signal acquisition, signal processing (which includes preprocessing, feature extraction, classification / detection, and post processing), application interface and an output device or application (left part of Figure 2; see also Wolpaw et al., 2002). For the experiments reported here, the Graz-BCI system was used (for details see Pfurtscheller et al., 2006c). It consisted of a biosignal amplifier (gBSamp, g.tec medical engineering, Graz, Austria), one data acquisition card (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 (Scherer, 2004), 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 (BioSig, 2010). In the case of an ERD BCI band power (BP) features were estimated from the ongoing EEG by digitally band-pass filtering the EEG recordings

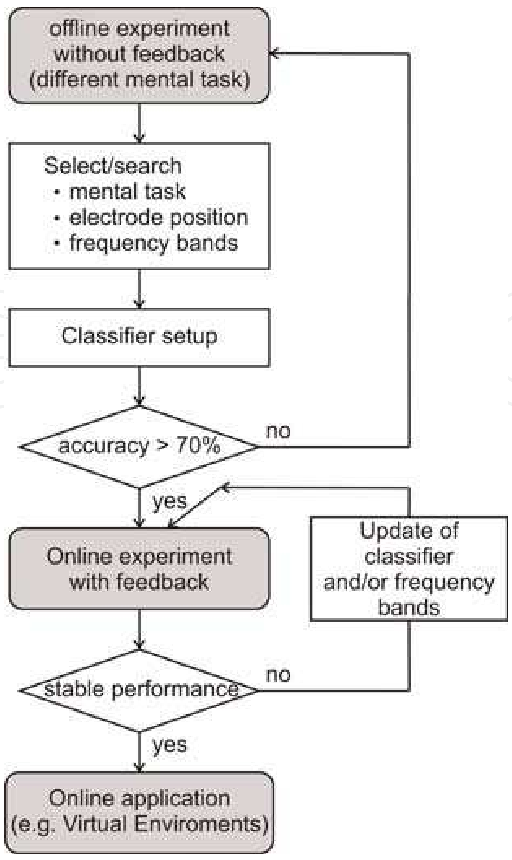


Fig. 3. General workflow of an experiment with a motor imagery-based BCI.

(Butterworth IIR filter of order 5) and squaring and averaging the samples over the past second. Finally, the logarithm was computed from this time series. To distinguish between the two motor imagery tasks, Fisher's linear discriminant analysis (LDA, Bishop, 1995) was applied to the BP estimates (sample-by-sample).

In the case of a SSVEP BCI, after calculation of the power spectrum, the first, second and third harmonic components are individually defined for each target frequency. For selecting one class, the sum of all its harmonic frequency components need to be larger than that of the other classes (for details see Müller-Putz et al., 2005).

The philosophy of the Graz-BCI is to use as few electrodes as possible for online experiments, which makes the BCI both, more comfortable and easier to apply, especially for subjects out of laboratory (e.g. at home or in working space). In all of the 4 experiments reported, EEG was recorded with an electrode cap (Easycap, Germany) fitted to the subject's head. EEG electrodes were mounted bipolarly over the sensorimotor cortex (ERD BCI) or over the occipital cortex (SSVEP BCI). The EEG was amplified (power-line notch filter was activated), band pass filtered between 0.5 and 100 Hz (EEG acquisition and preprocessing block, see Figure 2, left part) and recorded with a sampling frequency of 250 Hz.

5. Walking from thought - impact of immersive environments

The goals of the first study were: (i) to demonstrate that it is possible to move forward – "to walk" – within a VE (e.g. a virtual street) without any muscular activity, using only the imagination of movements recorded with a BCI and (ii) to compare the influences of different feedback types (common BCI feedback versus VE feedback (HMD and CAVE)) on the BCI performance. Therefore, the results from three different feedback (FB) conditions were compared: First, the results of the standard BCI with a simple bar graph; second, using a head-mounted display (HMD) as a FB device; and finally, using a highly immersive "CAVE" projection environment (see Figure 4a). In case of the HMD and CAVE conditions, the idea was to use the imagination of foot movement to walk through the VE, based on a synchronous BCI paradigm. The subject was instructed by a cue to imagine a right hand movement (single beep) or a foot movement (double beep). Three healthy volunteers participated several times over 5 months in this study. The task given to each participant was to walk to the end of a virtual street (see Figure 4a), and only in the case of successful foot motor imagery would a motion occur (for further details see Leeb et al., 2006; Pfurtscheller et al., 2006a). Correct classification of foot motor imagery was accompanied by forward movement at a constant speed in the virtual street, whereas a correct classification of hand motor imagery stopped the motion. Incorrect classification of foot motor imagery resulted in halting, and incorrect classification of hand motor imagery in backward motion (same speed). The walking distance was scored as "cumulative achieved mileage" (CAM, Leeb & Pfurtscheller, 2004; Leeb et al., 2006), which was the integrated forward/backward distance covered during foot movement imagination and was used as the performance measurement. So the BCI output of the online classification was either used to control the length and orientation of the bar graph feedback (control condition) or to move through a virtual street (HMD or CAVE condition). The CAM performances of the bar graph feedback experiments were simulated offline to enable comparison.

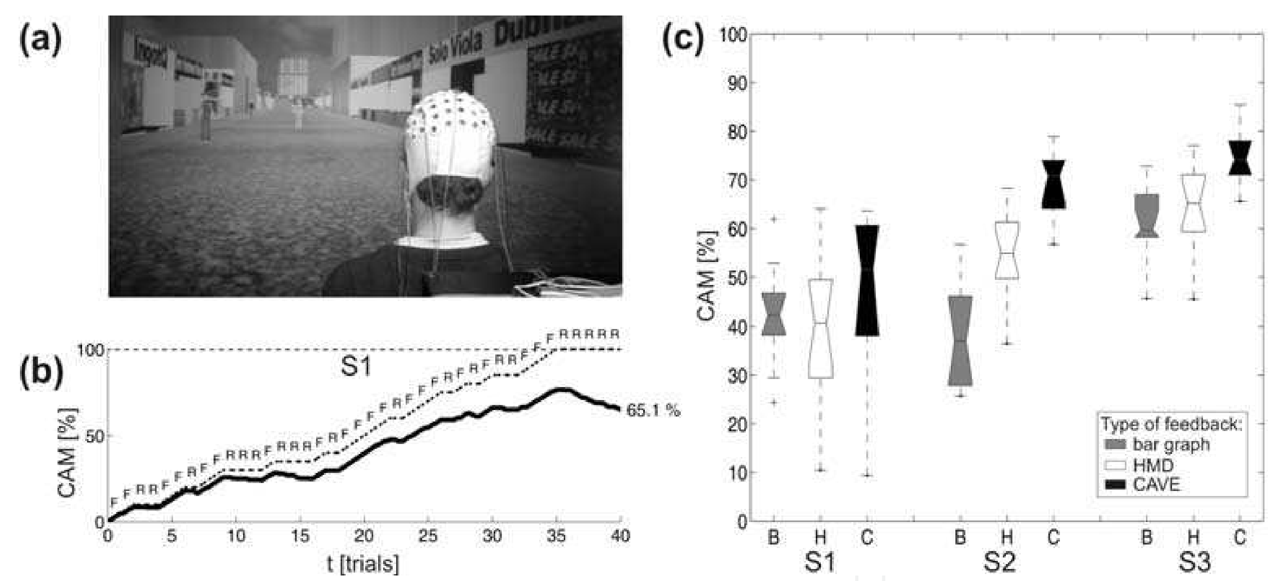


Fig. 4. (a) Participant in the virtual main street with shops and animated avatars. The subject wears an electrode cap and shutter glasses. (b) Examples of task performances displayed in the theoretical possible CAM (dashed line) and the real CAM (full line) of one run of one subject. The cue class indicated is written above the line. Due to the random cue sequence, each participant had a different theoretical pathway (dashed line). (c) Boxplot of all achieved CAMs of all subjects and feedback types. The diagram consists of 3 groups, each corresponding to a subject. Within these groups the left plots corresponds to standard bar-graph feedback (B), the middle to HMD feedback (H) and the right one to CAVE feedback (C). Modified from Leeb et al. (2007c).

The CAM of an example result of subject S1 (session 2, run 4) is plotted in Figure 4b. Both the theoretically possible CAM (dashed line) and the real achieved CAM (full line) are plotted. 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 %. It is almost impossible to achieve the maximum attainable CAM of 100 %, because even a small procrastination or hesitation reduces mileage.

All the subjects were able to walk through the virtual street, and the resulting BCI performance in the VR tasks was comparable to standard BCI recordings. The use of VR as feedback stimulated the participant's performances and provided motivation. All the subjects achieved their best results within the CAVE and the worst in the standard BCI conditions. The mean achieved CAM of all participants and condition is plotted in Figure 4c. Two participants showed an increase over the condition, but participant S1 achieved worse results with the HMD (for further details see Leeb et al., 2006).

These data indicate that foot motor imagery is a suitable mental strategy to control events within the VEs. Imagination of feet movement is a mental task which comes very close to that of natural walking. In the CAVE condition (highest immersion) the performance of two participants was especially outstanding (up to 100 % BCI classification accuracy of single trials), although we observed a variability in the classification results between individual runs.

6. Exploring a virtual apartment using an ERD-based BCI

The second study shows that ten naive subjects can be trained in a synchronous paradigm within 3 sessions to navigate freely through a virtual apartment (see Figure 5a), whereby, at every junction, the subjects could decide on their own how they wanted to explore the VE. The very important and crucial step away from a synchronized or cue-based BCI and from laboratory conditions towards real world applications is performed in this experiment. The virtual apartment was similarly designed to a real world application, with a goal-oriented task, a high mental workload and a variable decision period for the subject. All the subjects were able to perform long and stable motor imagery over a minimum time of two seconds (for further details see Leeb et al., 2007b).

In this paradigm, only the start of the decision period was indicated with a “neutral” cue consisting of two arrows (see Figure 5b). The subject could decide for him/herself which motor imagery he/she wanted to perform and therefore which direction he/she wanted to select, but walking was only possible along predefined pathways through the corridors or rooms. The subject received feedback by viewing the size of the arrows, which were modulated depending on the BCI classification output. 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. 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. 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 route through the maze-like apartment (see Figure 5a). The performance error was calculated by dividing the number of wrong decisions by the total number of junctions.

Each of the ten participating subjects performed 12 runs of variable duration in the virtual apartment. All the 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 the 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 route through the maze-like apartment (see Figure 5a). Only one target was given in the first two runs, 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 total.

For comparison, synchronous BCI sessions with a standard bar-graph feedback were performed before and after the sessions with the virtual apartment, whereby the experiments with the virtual apartment were performed in front of a normal TFT monitor (TFT) and within an immersive virtual environment (iVE). In Figure 5c, the mean and standard error over all subjects is given and the statistical differences between the sessions are marked. All the 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 subjects noted that the task in the virtual apartment was much harder compared to the prior feedback training, because it was not only necessary 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 (for further details see Leeb et al., 2007b). According to our hypothesis, we found that the performance improves (that is, reduced error) over the sessions, and the lowest error was found during the sessions with virtual feedback. The slight but stable performance improvement of all subjects is very well known as the training effect (Pfurtscheller & Neuper, 2001; Wolpaw et al., 2002).

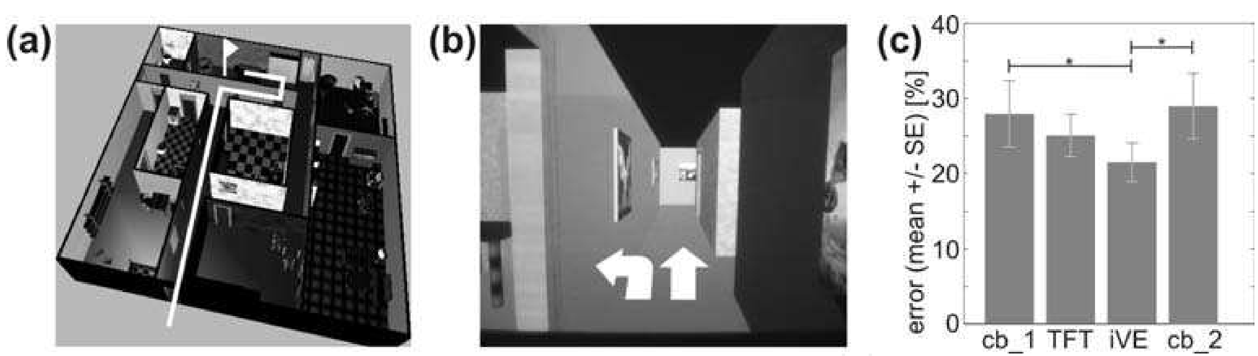


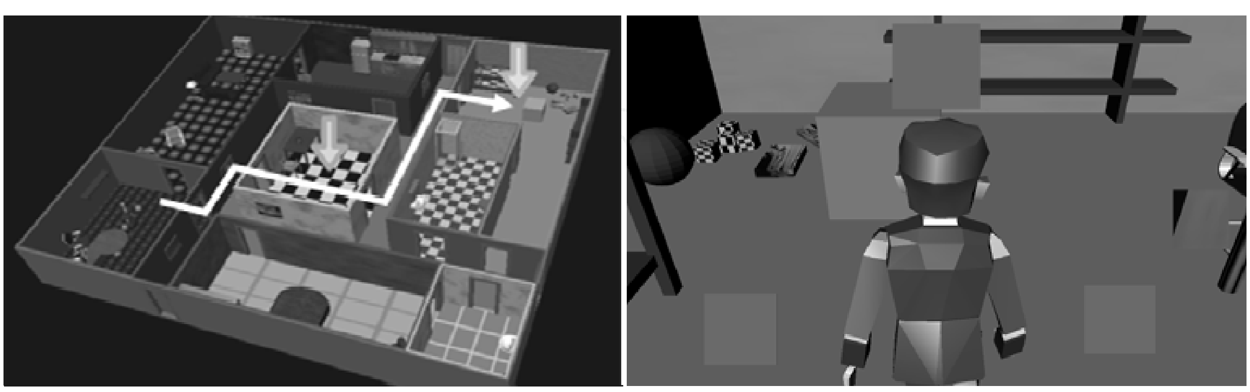
Fig. 5. (a) View into the virtual apartment, with one possible pathway plotted in white. The target room is marked with a small flag pole (in this example, the room at the upper end of the apartment). (b) First-person view of the virtual apartment with two arrows indicating the possible directions to go ("neutral cue"). (c) Mean ± standard error (SE) over all subjects of the integrated classification error and performance error. The asterisk (* p<0.05) shows statistically significant post-hoc differences. Cb_1 and cb_2 are the two sessions with standard BCI feedback before and after the VR sessions. TFT is the session with VR feedback presented on a normal TFT monitor and iVE in an immersive environment. Modified from Leeb (2008).

7. Exploring a virtual apartment using an SSVEP-based BCI

Another study involving seven healthy participants (see Faller et al., 2010) presented an even more flexible, asynchronous navigation paradigm within the same apartment scenario as in Leeb et al. (2007b) using an SSVEP-based BCI. The participants were instructed to navigate an avatar to two waypoints (see Figure 6a) along a given path in two runs, by alternately focusing attention on one of three visual stimuli that were flickering at the different frequencies 12, 15 and 20 Hz. Successful classifications of the according classes triggered the associated commands (i) turn 45° left (ii) turn 45° right and (iii) walk one step ahead.

In contrast to the work presented in Chapter 6, this system requires minimal setup and training time and offers faster, more accurate control, with the trade-off that it requires the user to visually fixate certain stimuli in order to communicate a control signal. The stimuli were presented directly within the 3D environment (see Figure 6b). Compared to systems that rely on external stimuli (e.g. LEDs), this approach is more dynamic and allows the user to better focus on goal-directed interactions and deal with a higher mental workload in the task.

Six out of seven subjects were able to navigate to the first waypoint in the first run halfway through the apartment. Five participants successfully reached the second waypoint in the second run. The average positive predictive value (precision, PPV = TP/(TP+FP), whereby TP stands for true positive and FP for false positive detections) over all participants was 91.7 ± 9.9 %, which resulted in an average of 6.5 ± 2.3 TP and 0.4 ± 0.4 FP activations per minute given a dwell-time of 1.5 s and a refractory period of 4s. These fixed temporal restrictions do of course limit the number of possible control commands per minute. However, some factors other than speed may be more important for the user. For instance, choosing a higher refractory period (Townsend et al., 2004) makes the SSVEP BCI easier to use, more likely to provide effective communication for a broader population of users, more reliable, and less fatiguing. This system demonstrates a virtual feedback environment that allows both disabled and healthy users to seamlessly communicate and interact through an intuitive, natural and friendly interface.



(a) (b)

Fig. 6. (a) Overview of the apartment showing the path along the two waypoints (marked by the arrows) that the participants are supposed to reach in the runs 1 and 2 respectively. (b) Screenshot of an in-game scene, showing the avatar in third person perspective along with the three navigation stimuli on the left, the right and over the avatar's head.

8. Moving a wheelchair in VR

Finally, we report on a 35 year old male tetraplegic subject. After a traumatic injury of the spinal cord in 1998, he has a complete motor and sensory lesion below C5 and an incomplete lesion below C4. During an intensive training period of approximately 4 months, he learned to control the cue-based Graz-BCI (details about this training are reported elsewhere (Pfurtscheller et al., 2000). Specifically, the midcentral focused beta oscillations with a dominant frequency of approximately 17 Hz allowed a brain-switch like application and control of a VE (recorded close to Cz, foot representation area). Only one single EEG channel was recorded bipolarly at Cz (foot representation area). One single logarithmic band power feature was estimated from the ongoing EEG (see Figure 7b-c). A simple threshold (TH) was used to distinguish between foot movement imagination (IC) and rest (INC). For further details see Leeb et al. (2007a).
The tetraplegic participant was placed with his wheelchair in the middle of a multi-projection based stereo VR system ("CAVE"). The VE used was a virtual street with shops on both sides (Leeb et al., 2006) and populated with 15 avatars, who were lined up along the street (see Figure 7a). The participant was instructed to "move" from avatar to avatar towards the end of the virtual street (65 length units) by movement imagination of his paralyzed feet. Only when foot MI was detected (IC) did the subject move forward (see Figure 7d, walking speed 1.25 units/second). Every time he was about to pass an avatar, he had to stop very close to it. The avatar started talking to the subject if he was standing close and still to it for one second. Each avatar was surrounded by an invisible communication

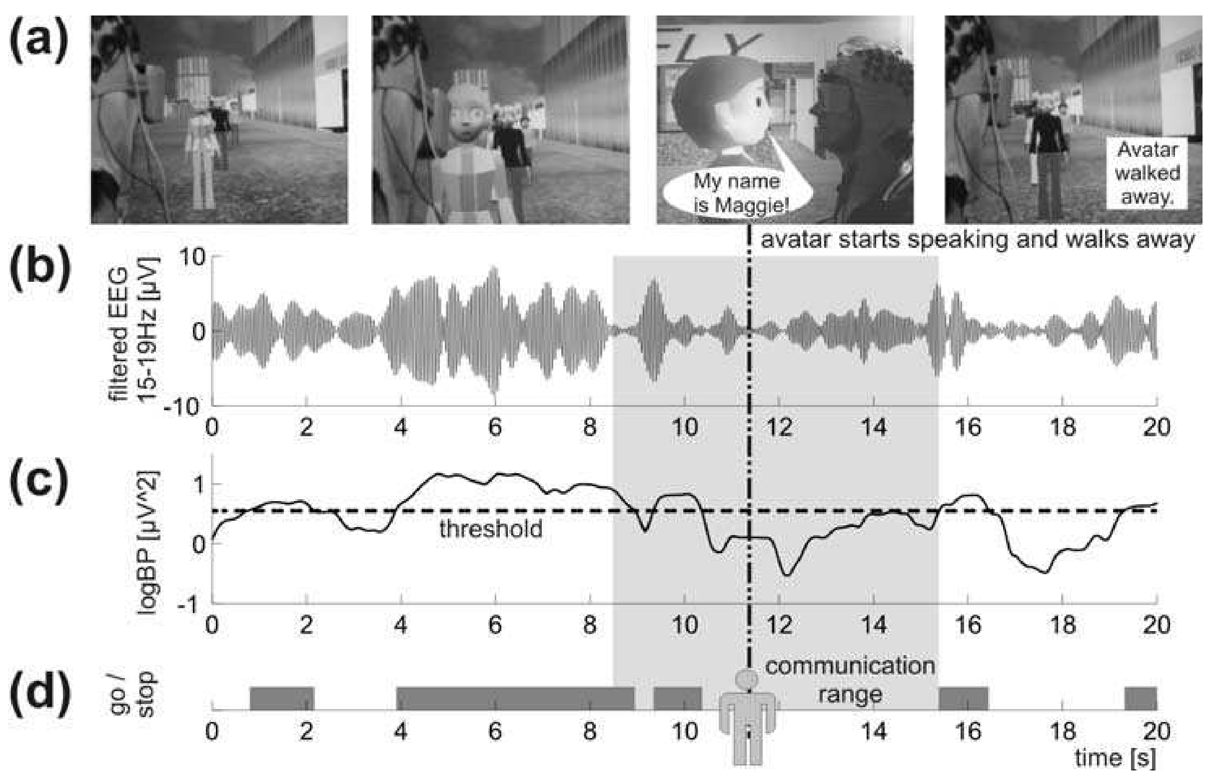


Fig. 7. (a) Picture sequence before, during and after the contact with an avatar. (b) Band-pass filtered (15–19 Hz) EEG and (c) logarithmic band power time course with threshold. (d) Indicated periods of moving and stopping. The contact with the avatar occurred at second 11.4. Modified from Leeb (2008).

sphere (0.5 – 2.5 units) and the subject had to stop within this sphere. The size of the sphere approximated the distance for a conversation in the real world. The avatar started talking to the subject if he was standing still for one second within this sphere. After finishing a randomly chosen short statement (like: "Hi", "My name is Maggie", "It was good to meet you"…), the avatar walked away. Communication was only possible within the sphere; if the subject stopped too early or stopped too close to the avatar, nothing happened. After a while, and with his own free will, the subject could imagine another foot movement and started moving again towards the next avatar, until the end of the street was reached.
The tetraplegic subject performed ten runs on two days, and he was able to stop at 90 % of the 150 avatars and talk to them. In four runs, he achieved a performance of 100 %. In 11 of the 15 missed avatars (of all runs), the subject stopped within the communication range, but the stopping time was too short (between 0.08 to 0.88 s mean ± SD = 0.47 s ± 0.27 s).
In an interview after the experiment, the patient confirmed that "moving" occurred only during periods of foot motor imagery, but he reported that it was hard to stop precisely. When the avatars were placed very laterally, it was especially hard to find the correct distance to the avatar. Concerning the experience with the interaction, he mentioned that "*It has never happened before, in the sense of success and interaction. I thought that I was on the street and I had the chance to walk up to the people. I just imagined the movement and walked up to them. However, I had the sensation that they were just speaking but not talking to me...*" He said that he had the feeling of being in that street and forgot that he was in the lab and people were around him. "*Of course the image on the CAVE wall didn't look like you or me, but it still felt as if I was moving in a real street, not realistic, but real. I checked the people (avatars). We had 14 ladies and 1 man.*" The subject stated that he felt surprised as one avatar walked through him; he wanted to get out of the way, to go backwards. This suggests that the subject felt very absorbed in the virtual reality environment.
This work demonstrated for the first time that a tetraplegic subject, sitting in a wheel chair, could control his movements in a VE by the usage of a self-paced (asynchronous) BCI based on one single EEG recording (for further details see Leeb et al., 2007a). The mentally induced beta oscillation in our patient is a unique phenomenon and probably the result of the intensive and long-lasting BCI feedback training with the goal of achieving control over brain waves. The use of visually rich and stimulating VE, involving avatars that were interacting with the subject, accounted for a diverse and challenging experimental paradigm. The simulation power of the VE ensured that he had the sense of being in the street and going to the people; therefore the experiment was similar to a task in a real street.
VEs are especially attractive for a person who is wheelchair-bound. First, simply using a VE can give such persons access to experiences that may be long forgotten (or which they have never had). The fact that the subject could still perform feet motor imagery, years after an injury that rendered him unable to use his feet, is a testament to the plasticity of the human brain (see also Kübler et al., 2005). Another advantage here is that VEs can be used to create virtual prototypes of new navigation or control methods, and give potential users experience of them in a safe environment before they are ever physically built.

9. Importance of VR feedback in BCI research

The increasing availability of VR technology has generated a high interest in studying BCI interaction with VEs.

Compared to traditional, abstract interfaces like mouse or keypad, BCI systems could potentially promise a more direct and intuitive way of interacting and thereby overcome some limitations of navigating within VEs (Usoh & Slater, 1995). This is especially obvious for *stimulus-dependent* BCI-VR systems (Figure 1b), where users can control appliances in the VE by simply directing their eye gaze and/or focus of attention towards the desired element (e.g., looking at the TV to switch it on, looking at the door to open it; Allison et al., 2008). In a typical *independent* BCI paradigm (Figure 1a) as described above, users learn to direct, e.g., a computer cursor towards a highlighted target via certain changes of specific EEG features. To accomplish this task, each participant develops a specific mental strategy to modify the relevant brain signals and use a BCI effectively. As ERD BCIs mostly rely on motor imagery, the mental process of imagining different types of movements offers an intuitive way of VE control like, for example, imagining foot movements for moving forward in a VE (Leeb et al., 2007a; Pfurtscheller et al., 2006a). A further advantage of using sensorimotor rhythms in BCI-based VE control is that they are typically modulated by motor activity (including both actual and imagined movements), but unaffected by changes in visual stimulation. Therefore people can use an ERD BCI while performing other visual tasks. Indeed, we have successfully shown that people can use an ERD BCI (based on motor imagery) at the same time as an SSVEP BCI (based on visual attention) (Allison et al., 2010; Brunner et al., 2010; Pfurtscheller et al., 2010a; 2010b).

Furthermore, research that explores BCI training in VEs is important for many reasons. VEs can help focus the training on the specific target application. For example, different training settings and paradigms may be more or less efficient, depending on whether the user's task is to select certain characters or icons for communication, control a neuroprosthesis to restore grasping, or navigate a wheelchair in a realistic environment. Moreover, it is a matter of ongoing research whether BCI training in stimulus-rich virtual environments is more effective than the standard training procedure using simple, more or less abstract, visual cues and feedback stimuli. The literature suggests that a realistic VE enhances the feeling of presence, task performance and also cortical activation (Jäncke et al., 2009; Lee and Kim, 2008; Slater et al., 2002). Combining BCI and VR technologies can lead to highly realistic and immersive BCI feedback scenarios that make participants more engaged and motivated. Thus, it is not unexpected that a rich visual representation of the feedback signal, such as a 3-dimensional video game or VE, may facilitate learning to use a BCI (Leeb, 2008; Pineda et al., 2003; Ron-Angevin et al., 2005).

The feedback is a very important component of the BCI as it provides the user with information about the efficiency of his/her strategy and enables learning. The studies mentioned above support realistic and engaging feedback scenarios which are closely related to the specific target application. However, the processing of such a realistic feedback stimulus may also interfere with the mental motor imagery task, and thus might impair the development of BCI control (Neuper et al., 2009). This could be the case when the realistic feedback presentation showing (for instance) a moving visual scene is not compatible with the specific mental action the user creates to induce the relevant brain signals. Therefore, the mutual interaction between a mentally simulated movement (for BCI control) and simultaneous watching of a moving scene should be further investigated in future studies.

Another interesting aspect is that mental simulation of movement (motor imagery) results in cardiovascular changes explained by two factors, i.e. function of anticipation of movement and central preparation of movement (Damen & Brunia, 1987; Oishi et al., 2000). The heart rate (HR) generally decreases during motor imagery in laboratory conditions without VR feedback (Leeb, 2008; Pfurtscheller et al., 2006b), but can be increased during effortful imagery and/or enhanced mental effort (Decety et al., 1991), such as during VR feedback in BCI experiments (Pfurtscheller et al., 2006b; 2008a). This underlines the importance of VR feedback in modifying emotional experiences and enhances autonomic and visceral responses. The HR changes can be in the order of several beats per minute and therewith used to increase the classification accuracy of an ERD-based BCI when both the EEG and the HR are analyzed simultaneously.

10. Concluding remarks

One important component of a BCI system is feedback. VR offers a powerful possibility not only to rehearse scenarios that are otherwise too dangerous or expensive to set up, such as simulation of wheel chair movement, but also to modify emotional experiences and enhance therewith autonomic responses as e.g. heart rate changes. This opens a new way to improve the performance of a BCI by simultaneously analyzing and classifying brain and heart rate changes and to realize a "hybrid BCI" (Pfurtscheller et al., 2010a). Furthermore, VR environments may offer numerous other benefits, such as reduced training time, improved classification accuracy, increased sense of immersion/presence in an artificial setting, and reduced boredom or fatigue.

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Technological advancement in graphics and other human motion tracking hardware has promoted pushing "virtual reality" closer to "reality" and thus usage of virtual reality has been extended to various fields. The most typical fields for the application of virtual reality are medicine and engineering. The reviews in this book describe the latest virtual reality-related knowledge in these two fields such as: advanced human-computer interaction and virtual reality technologies, evaluation tools for cognition and behavior, medical and surgical treatment, neuroscience and neuro-rehabilitation, assistant tools for overcoming mental illnesses, educational and industrial uses In addition, the considerations for virtual worlds in human society are discussed. This book will serve as a state-of-the-art resource for researchers who are interested in developing a beneficial technology for human society.