23 Combining BCI and Virtual Reality: Scouting Virtual Worlds

Robert Leeb, Reinhold Scherer, Claudia Keinrath, and Gert Pfurtscheller
Laboratory of Brain-Computer Interfaces
Institute for Knowledge Discovery
Graz University of Technology
Krenngasse 37, A-8010 Graz, Austria

Doron Friedman
Department of Computer Science
University College London
Gower Street
WC1E 6BT London, United Kingdom

Felix Y. Lee and Horst Bischof
Institute for Computer Graphics and Vision
Graz University of Technology
Inffeldgasse 16, A-8010 Graz, Austria

Mel Slater
Department of Computer Science
University College London
Gower Street
WC1E 6BT London, United Kingdom

Department Llenguatges i Sistemes Informàtics
Universitat Politècnica de Catalunya
E-08028 Barcelona, Spain

23.1 Abstract

A brain-computer interface (BCI) is a closed-loop system with feedback as one important component. Dependent on the BCI application either to establish communication in patients with severe motor paralysis, to control neuroprosthesis, or to perform neurofeedback, information is visually fed back to the user about success or failure of the intended act. One way to realize feedback is the use of virtual reality (VR). In this chapter, an overview is given of BCI-based control of VR. In addition, four examples are reported in

more detail about navigating in virtual environments with a cue-based (synchronous) and an uncued (asynchronous) BCI. Similar results in different virtual worlds with different types of motor imageries could be achieved, but no significant differences in the BCI classification accuracy were observed between VR and non-VR feedback. Nevertheless, the use of VR stimulated the subject's task performances and provided motivation.

23.2 Introduction

Brain-computer interface (BCI) technology deals with the development of a direct communication channel between the human brain and machines that does not require any motor activity (Wolpaw et al. (2002)). This is possible through the real-time analysis of electrophysiological brain signals recorded by electroencephalogram (EEG) or electrocorticogram (ECoG). Voluntary mental activity (e.g., a sequence of thoughts) modifies bioelectrical brain activity and consequently the EEG and ECoG. A BCI is able to detect such changes and generate operative control signals. Particularly for people suffering from severe physical disabilities or who are in a "locked-in" state, a BCI offers a possible communication channel.

Before a BCI can be used for control purposes, several training sessions are necessary. Two sorts of learning can occur in BCI: (1) the users learn to control their own brain activity (operant conditioning) and (2) the machine learns to recognize mentally modified brain patterns (machine learning). Operant conditioning is exploited by feeding back raw signals, or extracted parameters, as real-time changes to the user. Machine learning employs adaptive algorithms to detect brain patterns. For this purpose, signals first need to be recorded and analyzed, and a classifier must be setup, before feedback can be provided. The duration of the training varies strongly from subject to subject and can last from several hours to many months; therefore, a fundamental goal of BCI research is to reduce this period.

The presentation of visual feedback plays a major role during the training (Neuper and Pfurtscheller (1999)). Visual input has a strong impact on motor cortex activity (Rizzolatti et al. (2001)). Not only the primary and higher order visual areas are activated, but also the activities in motor and premotor areas are affected. This raises the question of which type of visualization best facilitates online learning and therefore improves the performance of a BCI system. Virtual reality (VR) might be a useful tool in providing visual feedback since it provides a class of user interfaces able to create "realistic" artificial (virtual) environments by means of three-dimensional, usually stereoscopic, computer graphics. The immersion into the virtual environment (VE) should allow users to be shielded from the outside world (Slater et al. (2002)) and therefore be able to focus on the required mental task. The use of VR as feedback medium may be more motivating and entertaining than standard feedback representations and therefore represents a crucial component during learning processes. The field of presence research (Slater and Usoh (1993)) aims to create VR where people feel and respond similarly to an equivalent real-world situation. If a VR keeps this promise, then feedback would be as natural as a real-world feedback could be. For example, users would control a locomotion device and actually feel themselves moving.

The technological progress in the past decade has made VR systems attractive for various research fields and applications ranging from aviation and military applications to simulation and training programs (where real-life training is too expensive or difficult to monitor and control), and from psychotherapy (Huber (2005)) to medical surgery. In particular, the area of medical rehabilitation exploits the possibilities and advances available from VR systems. Precisely, it encourages the rehabilitation of motor functions (Holden (2005)) including stroke rehabilitation (upper and lower extremity training) (Jack et al. (2001)), spatial and perceptual motor training, Parkinson's disease, orthopedic rehabilitation (Girone et al. (2000)), balance training, and wheelchair mobility (Webster et al. (2001)). A major finding in this field is that people with disabilities can perform motor learning in VR that can then be transferred to reality. In some cases it is even possible to generalize to other untrained tasks including improved efficiency of virtual training and learning (Holden (2005); Todorov et al. (1997)). It is important to note that VR is not a treatment by itself, and therefore it is impossible to study whether it is effective or not for rehabilitation. Although VR rehabilitation was undertaken for patients with acquired brain injury or damage with some success (Rose et al. (2005)), it is rather a new technological tool, which may be exploited to enhance motor retraining. Finally, virtual reality technology has positively influenced many other fields in neuroscience (Sanchez-Vives and Slater (2005); Tarr and Warren (2002)).

This chapter focuses on the benefits and impacts of such a technology on brain-computer interface (BCI) research, starting with a description of the background and related work and followed by a discussion of several results from various applications of BCI-based control of VR.

23.3 Background and Related Work

This section introduces two kinds of research in the context of virtual environments (VEs). Previous research has been established suggesting that a BCI may be used to control events within immersive VEs. Additionally, a second line of research is presented that did not use VEs but related technologies such as video games.

23.3.1 BCI and Immersive Systems

Nelson et al. (1997) were interested in BCI as a potential application for increasing the effectiveness of future tactical airborne crew stations. CyberLink is an interface that uses a combination of EEG and electromyographic (EMG) biopotentials as input signals in a single-axis continuous control task. The participants used the interface to navigate along a predetermined flight course that was projected onto a 40-foot diameter dome display. Continuous feedback was provided by a graphical head-up display. Participants were not given any BCI instructions. Scores of effective task performance gradually increased with training.

Bayliss and Ballard (2000) used the P300-evoked potential (EP) component, a positive waveform occurring approximately 300–550 ms after an infrequent task-relevant stimulus.

They used a head mounted display – (HMD) based VR system. Subjects were instructed to drive a modified go-cart within a virtual town and stop at red lights while ignoring both green and yellow lights. The red lights were made to be rare enough to receive full attention, which usually causes a clear P300 component. Results showed that a P300 EP indeed occurs at red lights and was absent at yellow lights, with recognition rates high enough to serve as a suitable BCI communication medium. In further research, Bayliss (2003) continued exploring the usage of the P300 component in VR. Subjects were asked to control several objects or commands in a virtual apartment: a lamp, a stereo system, a television set, a "Hi" command, and a "Bye" command, in several nonimmersive conditions, and with an HMD. Using BCI, subjects could switch the objects on and off or cause the animated character to appear or disappear. The BCI worked as follows: Approximately once per second a semitransparent sphere appeared for 250 ms on a randomly selected object. Subjects were asked to count the flashes on a specific object (to focus their attention) and to make the stimulus task-related, which is necessary to obtain a P300 component. During every run a written text instruction on the bottom of the screen indicated the goal object. The subject had to count the flashes for that object only and a visual feedback was given when the goal was achieved, that is, when a P300 event was recorded. Subjects were able to achieve approximately three goals per minute. Bayliss found no significant difference in BCI performance between VR and the standard computer paradigm, but individually most subjects preferred the VR environment.

Ron Angevin et al. (2004) proposed a training paradigm using VR techniques to avoid early fatigue from the learning process. In this work they used a virtual driving simulator inside an HMD, whereby the subjects had to control the car's left/right position to avoid an obstacle placed on the street by the imagination of hand movements. Five out of eight subjects were able to achieve suitable results. They noted that the control group (standard BCI feedback) reacted faster than the VR group; however, the VR group achieved less error than the control group.

Finally, the Graz-BCI also was used to control VR applications. Leeb et al. (2003, 2005) described the possibility of exploring a virtual conference room by the imagination of left and right hand movements using an HMD setup with success rates up to 100 percent. In further research, Leeb and Pfurtscheller (2004) and Pfurtscheller et al. (2006b) reported on an experiment concerned with subjects moving through a virtual environment by thought ("walking from thought") based on the imagination of foot movements, whereby after an HMD training, the subjects were able to move through a virtual street displayed on a highly immersive projection environment.

23.3.2 BCI-Based Control of Game-Like Environments

Middendorf et al. (2000) harnessed the steady-state visually evoked potential (SSVEP), a periodic response elicited by the repetitive presentation of a visual stimulus, as a communication medium for the BCI. One of the presented experiments involved controlling a flight simulator, where the roll position of the flight simulator was controlled with BCI. The "airplane" rolled right or left depending on the SSVEP amplitude over a half-second period. Most operators were able to successfully control the airplane after thirty minutes of training.

Lalor et al. (2005) used the SSVEP as a control mechanism for a 3D game. Players had to intervene when a character walking on a thin rope lost balance by looking at checkerboard images on two sides of the animated image. They reported robust BCI control and attributed relative success to motivation. Both approaches are based on visually evoked responses, which typically force the subject to focus visual attention and therefore may be unnatural.

Pineda et al. (2003) used the similarity or the difference in the μ activity (8–12 Hz) over the two hemispheres to control movements in a video game environment. After ten hours of training the subject played a high-resolution 3D first-person shooter game on a desktop monitor, whereby the forward and backward movements were controlled by the keyboard but the left and right movements were controlled by high and low μ, respectively.

Mason et al. (2004) applied their low-frequency asynchronous switch design (LF-ASD) to control a video game-like environment. The LF-ASD has been derived from signal characteristics observed in the 1–4 Hz frequency band of a feature vector based on nine electrodes over the primary and supplementary motor cortex. After a training session (six trials), a test with a simple video game was performed. A white circle (user's avatar) was moving with continuous speed over the monitor and was bouncing off obstacles (walls or pillars). An activation of the brain-switch would cause the avatar to turn left. Subjects self-reported an error (the avatar either failed to turn when intended or turned unintentionally) with a pneumatic sip-n-puff switch. They report that the performances of four able-bodied subjects and four subjects with high-level spinal cord injuries (level of injury between C3-4 and C5-6) were similar.

23.4 Combination of BCI and VR

23.4.1 Graz-BCI

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 (as described in chapter 4; Pfurtscheller and Neuper (2001); Pfurtscheller et al. (2003c)). In particular, hand and foot motor imagery makes it possible to realize a BCI (Pfurtscheller et al. (2005a)).

Over the sensorimotor hand and foot representation areas two (C3 and C4) or three (C3, Cz and C4) EEG-electrode pairs are placed according to the international 10-20 system (2.5 cm anterior and posterior to the named electrode positions). The ground electrode is positioned on the forehead. The EEG is bipolarly recorded at a bandwidth of 0.5–30 Hz from sintered Ag/AgCl electrodes and sampled with 250 Hz. For online classification, two frequency bands (logarithmic bandpower, BP) of the specific EEG channels are used. These features are classified with Fisher's linear discriminant analysis (LDA, Bishop (1995)) and transformed into a control signal (for details, see Pfurtscheller et al. (2005a)). For offline processing, all trials are visually controlled for artifacts and affected trials are excluded from further analyses.

To calculate the classifier setup, motor imagery data must be acquired for each subject. In general, one run consists of fourty trials in a randomized order, twenty trials for each type of imagery. The task is to perform a cue-dependent (synchronous) mental activity following a predefined, repetitive time-scheme. The visual cue, for example, an arrow pointing either to the left or right side, indicates the imagination of a left or right hand movement, respectively. The imagination has to be performed for a predefined period (usually 4 s, see figure 23.1b), followed by a random-length pause usually between 4 and 5 s. Afterward the classifier, trained with these trials, is subsequently used for the online feedback training. The task is to move the feedback cursor toward the direction indicated by the arrow by performing the same mental activity previously trained to do. By updating the classifier with this new data, the human brain and the classifier are mutually adapting (Pfurtscheller and Neuper (2001)). In the presented experiments, the classifiers were updated only after the first two feedback sessions, and afterward used for all further sessions.

The Graz-BCI consists of an EEG amplifier (g.tec, Graz, Austria), a data acquisition card (National Instruments, Austin, Texas, USA) and a commercial desktop PC running WindowsXP (Guger et al. (2001)). The BCI algorithms are implemented in MATLAB 6.5 and Simulink 5.0 (The MathWorks, Natick, Mass., USA) using rtsBCI and the open source package BIOSIG (by Schlögl et al.).

23.4.2 Virtual Environments

Virtual reality generates three-dimensional stereoscopic representations of computer-animated worlds. Present VR systems need either a large-scale display with shutter or polarization glasses, or an HMD to separate the two stereoscopic images generated for each eye of the observer. The basic idea is to let a user become immersed in a 3D scene. The highest immersion can be achieved in a multiprojection stereo-based and head-tracked VE system commonly known as a "Cave" (Cruz-Neira et al. (1993)). A special feature of any multiwall system is that the images on the adjacent walls are joined together seamlessly, 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 creation of the 3D virtual environment consisted of two consecutive steps: first the creation of a 3D model of the scene and second the generation of a VR-application that controls and animates the modeled scene. In our studies, the 3D modeling software packages Performer (Silicon Graphics, Mountain View, Calif., USA) and Maya (Alias, Toronto, Canada) were used. The experiments reported are performed with a Virtual Research V8 HMD (Virtual Research Systems, Aptos, Calif., USA) with a resolution of 640 x 480 pixels at a refresh rate of 60 Hz driven by VRjuggler, with a single back-projected wall and shutter glasses driven by Coin3D or the Studierstube Augmented Reality framework, or with a ReaCTor, a Cave-like system using the DIVE software (Frecon et al. (2001)) with CrystalEye (StereoGraphics, Beverly Hills, Calif., USA) stereo glasses. All VR systems have also the possibility to include tracking information, but because BCI experiments require a subject in a sitting position, no positional information had to be considered. Additionally, rotational information from the tracking system was ignored because rotation should be controlled by the BCI in the following Graz-BCI-specific VR applications.

23.5 Graz-BCI-Specific VR Applications

23.5.1 Study 1: Rotation in a Virtual Environment by Left- and Right-Hand Motor Imagery

In the first application, the imagination of left and right hand movement was applied to control VR feedback. For evaluation purposes three different conditions were compared: (1) a standard horizontal bar graph on a desktop monitor (Pfurtscheller et al. (2003c)), (2) a virtual conference room presented with an HMD (Leeb et al. (2005)), and finally (3) a virtual pub populated with animated avatars, including background music and chatter of the avatars (see figure 23.1a) in a Cave. The subject was either sitting in front of an LCD monitor, wearing an HMD, or sitting in the middle of this virtual pub.

Three subjects, two male and one female (23, 26, and 28 years old), participated repeatedly in this study over a period of seven months. The order of feedback conditions was standard bar graph, HMD, Cave, HMD, standard bar graph (see figure 23.1d–f). The participants were instructed to imagine left or right hand movements, depending on an acoustic cue (single or double beep). During the feedback time, the output of the classifier controlled either the length and the orientation of the horizontal bar graph in case of the standard BCI feedback, or the rotation angle and direction within VR. During the BCI experiments the cue was given at second 3 and the feedback was presented continuously for 4 s (see figure 23.1b) (Pfurtscheller and Neuper (2001)). The feedback on the screen was updated 25 times per second and either the length of the bar graph was changed or the rotation angle was modified. Thereby, the subject perceived the feeling of rotating with constant speed (24 degress/s) to the right and left depending on the imagined movement. In this way, the rotation information was integrated over one trial (cumulative feedback). The maximum achievable gyration was ± 90 degrees within one trial, increasing linearly to this maximum over the feedback time. A random classification would result in an expected rotation of 0 degress.

The mean rotation achieved by one exemplary subject (S1, HMD condition, session 4, run 6), is plotted in figure 23.1c by averaging all 20 trials for right hand imagination and all 20 trials for left hand imagination. In this run, the subject had problems with the right class during second 4.25 and 5; therefore, the rotation angle moved first to the left and afterward from a negative angle straight to the right side. The mean of the achieved rotation over all trials of this run is 70 degrees for right-hand and -79 degrees for left-hand motor imagery. The reason for the larger standard deviation (SD) at second 8 compared to second 5, for example, is due to the cumulative presentation of the results. The subjects obtained promising results with the three feedback systems. For comparison reasons, the rotational information of the runs recorded with standard BCI feedback were simulated offline and therefore these runs can be compared to the VR experiments. Subject S1 achieved the

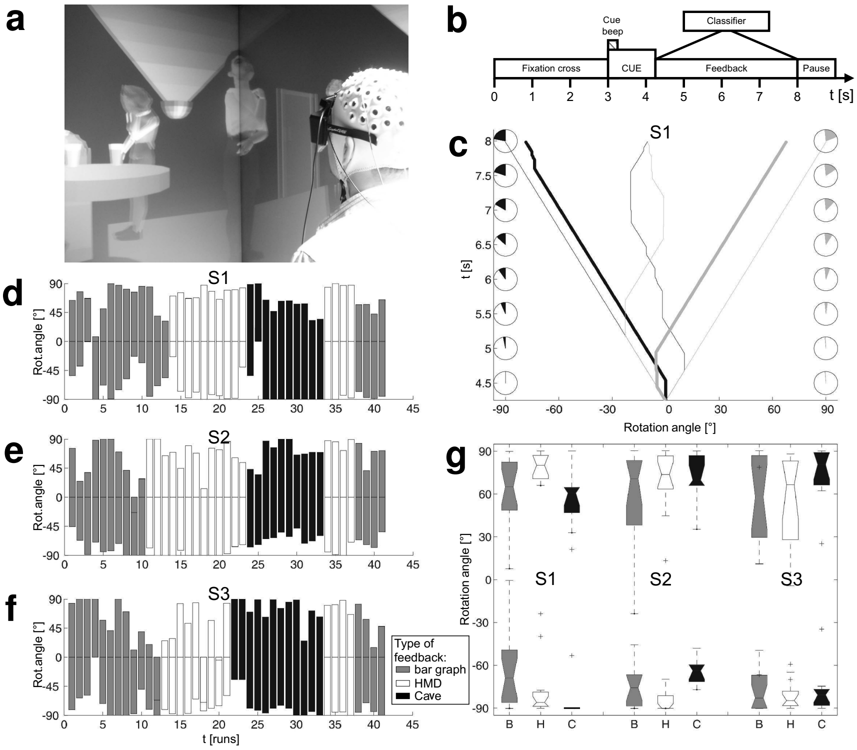

Figure 23.1 (a) Picture of a subject in the virtual pub room. The pub is populated with animated avatars (guests and barman). The subject wears shutter glasses and an electrode cap. (b) Timing of the used paradigm. Between seconds 3 and 4.25 the cue information is presented by an arrow pointing to the left, the right, or downward, depending on the motor imagery used. The cue information of the synchronous two-class BCI is also given acoustically as a single or double beep. In the case of feedback sessions, the classifier output is not presented until second 8. (c) Plot of the achieved rotation angle of one exemplary run of 40 trials of subject S1. Mean angles are plotted in thick and mean $\pm$ one SD in thin lines. Right-hand imagery is plotted in light and left-hand in dark colors. The maximum achievable angle is $\pm 90^\circ$ at second 8, whereby the two outer lines reach these points. The small circles on the left and right side are a more convenient illustration of the mean rotation angle at that specific time point, whereby the pie slices are the actually reached gyrations. (d)–(f) Achieved rotation angle over all runs for subjects S1, S2, and S3. Each vertical bar corresponds to the rotation angle of one run (final value of panel c), whereby the upper bar indicates the rotation to the right and the lower bar the rotation to the left. Runs with bar graph feedback are plotted in grey, with HMD feedback in white and Cave feedback in black. (g) Boxplot of all rotation angles of all subjects and feedback types, whereby the upper boxplot indicates the rotation to the right and the lower boxplot the rotation to the left. The diagram consists of 3 groups each corresponding to one subject. Within these groups the left plots correspond to standard BCI feedback B, the middle to HMD feedback H and the right one to Cave feedback C. Each boxplot has lines at the lower quartile, median, and upper quartile values.

best performance with HMD feedback and worst with standard bar graph feedback (see figure 23.1d and g). Subject S3 was best in Cave condition followed by HMD and bar graph (see figure 23.1f and g). Interestingly, no differences between HMD and Cave feedback could be found because some subjects performed better with HMD and some better with Cave feedback, but all subjects performed at least as well with VR feedback compared to standard bar graph feedback (see figure 23.1g). The number of trials contaminated with movement, muscle, or eye-movement artifacts were always between 0 and 5 out of 40 trials, but no differences between the various feedback conditions could be found.

Subjects noted that the virtual pub in the Cave feedback had two areas: The virtual characters concentrated in one area, whereas the other side of the room was empty. It did not even contain furniture (only a disco-style chandelier). Subjects reported that BCI control was more difficult in the empty space because no clear spatial information was obtained. Some subjects found the audio chatter in the Cave condition a bit distracting, but none of them reported problems in identifying the auditory cues.

23.5.2 Study 2: Moving Forward in a Virtual Street by Foot Motor Imagery

In this experiment, the imagination of foot movement was used to walk through a VE based on the previously applied BCI paradigm (see figure 23.1b). The subject was instructed to imagine a right hand movement (arrow to the right and single beep) or a foot movement (arrow pointing downward and double beep). Three healthy male volunteers aged 23, 28, and 30 years participated several times in this study. The task given to each participant was to walk to the end of a virtual street (see figure 23.2a) and in the case of successful foot motor imagery only, a motion would occur. Correct classification of foot motor imagery was accompanied by forward movement at constant speed (1.3 length units/s) in the virtual street, whereas a correct classification of hand motor imagery stopped the motion. Incorrect classification of foot motor imagery also resulted in halting, and incorrect classification of hand motor imagery resulted in backward motion (same speed). The walking distance was scored as a “cumulative achieved mileage” (CAM; Leeb and Pfurtscheller (2004)), which was the integrated forward/backward distance covered during foot movement imagination, and was used as performance measurement.

The output of the online classification was used either to control the length and orientation of the bar graph feedback or to move through a virtual street (HMD or Cave condition). The order of feedback conditions was as follows: standard bar graph, HMD, Cave, HMD, standard bar graph (see figure 23.2d–f). For comparison reasons, the CAM performances of the bar graph feedback experiments were simulated offline.

In figure 23.2b and c, the performed CAM of exemplary results of subject S1 (session 2, run 4) and subject S3 (session 2, run 5) are plotted. Both the theoretically possible CAM (dashed line) and the real-achieved CAM (full line) are plotted. Due to the different sequences of the twenty foot (F) and twenty right-hand (R) motor imageries, which were randomly distributed to avoid adaptation, the theoretical pathways are different in all pictures. Nevertheless, the number of trials for both classes is the same and therefore the maximum possible CAM also. A CAM of 100 percent corresponds to a correct classification of all fourty imagery tasks over the entire feedback time. A random classification

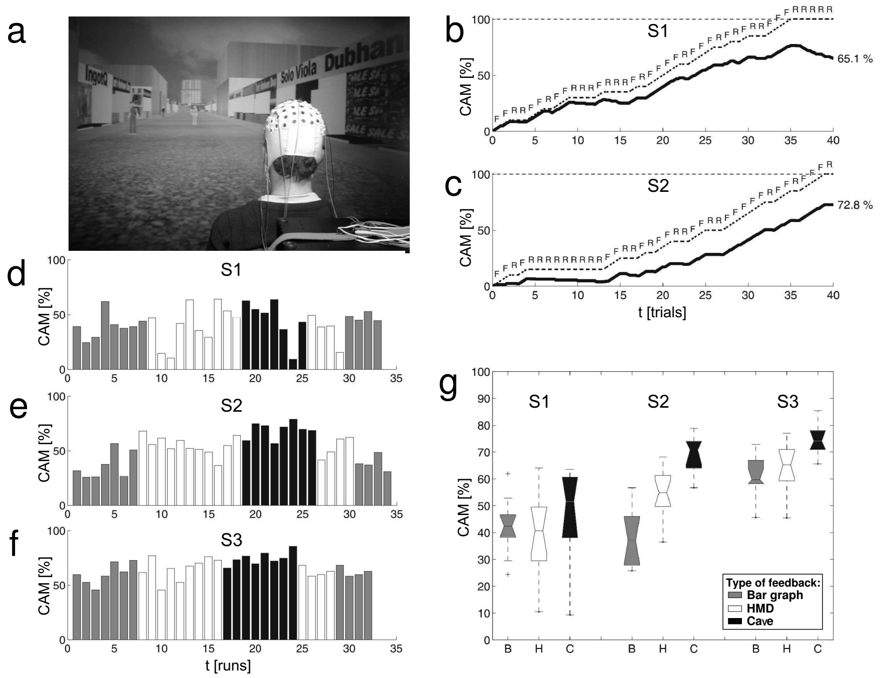

Figure 23.2 (a) Participant in the virtual main street with shops and animated avatars. The subject wears an electrode cap and shutter glasses. (b) and (c) Exemplary task performances displayed in the theoretical possible CAM (dashed line) and the real CAM (full line) of one run of two subjects. The cue class indicated is written above the line. Due to the random cue sequence, each participant had a different theoretical pathway (dashed line). (d)–(f) Achieved walking distances over all runs for subjects S1, S2, and S3. Each vertical bar corresponds to the CAM of each run (end value of picture b or c). Runs with bar graph feedback are plotted in grey, with HMD feedback in white and Cave feedback in black. (g) 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 BCI feedback B, the middle to HMD feedback H and the right one to Cave feedback C.

would result in an expected CAM of 0 percent. It is almost impossible to achieve the maximum attainable CAM of 100 percent, because every small procrastination or hesitation of the participant results in reduced mileage. In the example presented in figure 23.2b, a close-to-perfect performance at least up to trial 35 is shown, followed by a small breakdown. A possible explanation for the problems in the performance results of subject S3 (in figure 23.2c) could be that between trial 4 and 14 the same class performance was required, which is the “standing class” (right hand movement), but the participant was not able to remain stationary for such a long period. A similar effect can be observed at the end of the run plotted in the bottom row of figure 23.2b. A faster alternation between the two classes might achieve better results, but the sequence of cues was randomized automatically through each run.

All subjects were able to walk through the virtual city. The use of VR as feedback stimulated the participant’s performances. All subjects achieved their best results within the Cave and the worst in the standard BCI conditions (see figure 23.2g). In particular, subjects

S2 and S3 improved by using VR feedback (see figure 23.2e and f). Only subject S1 showed a different behavior, due to a high variability over the runs in the VR feedback (see figure 23.2d). One possible interpretation is that VR feedback amplifies both positive and negative feedback effects on the performance. The wrong-behaving rich visual feedback can modify the EEG activity and thereby result in a further deterioration of performance. It must be noted that during the Cave experiments, a competition arose between subjects S2 and S3, which might have influenced the performances positively.

The number of trials contaminated with electrode movement, muscle, or eye-movement artifacts were always less than six out of fourty trials, but trials with VR feedback had no more artifacts than the trials with standard feedback.

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 that comes very close to that of natural walking. 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 among individual runs occurred.

23.5.3 Study 3: Scouting through a Virtual Apartment

The next important step was to incorporate free will decisions (intentional control, IC) in a synchronous (cue-based) BCI. Although a predefined time window (with variable length) was used for feature extraction and classification, the user could choose which imagined movement to perform after each cue. In a pilot study, a virtual apartment (see figure 23.3a) was used as feedback presented on a single back-projected stereoscopic wall. In this 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 two directions that were indicated by a “neutral” cue consisting of arrows (see figure 23.3b). The size of the arrow was modulated depending on the BCI classification output, so the subject received feedback. The analysis was performed until a threshold was exceeded (huge arrow), and the subject was turned to the right, left, or straight. Afterward, the system automatically guided the subject to the next junction. Additionally, a small map of the apartment was inserted in the bottom right corner of the display. In this study a cue-based BCI was still used, but the cues were completely embedded in the given task or experiment and the duration of the trials was variable, depending on the performance of the subject only. Four naive subjects (three male and one female, between 21 and 27 years) without any prior BCI experience participated in this study. Before placing the subjects into the VE, two training sessions (each with four runs) without feedback and two sessions with feedback were performed. The resulting classification errors are presented in table 23.1.

Each subject performed eleven 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 five 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. In the first

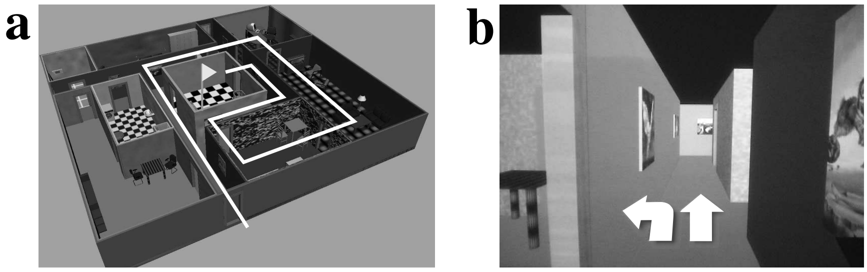

Figure 23.3 (a) View into a virtual apartment with one possible pathway. The target room is marked with a small flag pole (e.g., the room in the middle of the apartment). (b) First-person view of the virtual apartment with two arrows indicating the possible directions to go. The size of the arrow indicates the BCI classification output.

Table 23.1 Classification performance for each subject and each feedback type. The classification error in percent is given for training and standard feedback sessions, and the percentage of wrong turnarounds is given for sessions in the virtual apartment. The number of trials/junctions of these sessions are in brackets.

Subject	Training with no feedback		Standard feedback Session 1		Standard feedback Session 2		Virtual apartment	
S1	7.9%	(240)	1.9%	(160)	1.0%	(160)	8.8%	(96)
S2	18.2%	(240)	28.4%	(160)	17.0%	(160)	28.6%	(136)
S3	29.7%	(240)	32.8%	(160)	19.1%	(160)	25.2%	(206)
S4	26.4%	(240)	20.2%	(160)	15.9%	(160)	20.8%	(133)

four 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. Dividing the number of wrong decisions by the total number of turnarounds results into the classification performance of the VE task (see table 23.1). Different from the previous examples, the number of trials/decisions in a run varied depending on the chosen path. 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 2.2 and 5.9 s, with a mean $\pm$ SD of 2.9 $\pm$ 0.5 s. The naive subjects achieved a BCI classification error of less than 20 percent after two feedback sessions. Interestingly, two subjects revealed worse results within the first feedback session than they achieved in the training period without FB. However, the second feedback session resulted in reduced error. The subjects obtained comparable performances with the standard feedback (error rates between 1 and 33%) and the virtual apartment feedback (error rates between 7 and 23%). The subjects noted that the task in the virtual apartment was much harder compared to the prior feedback training because not only the "correct" imagination must have been performed, but also the shortest way had to be found. Despite the undefined trial length (the duration of the trial depended on how fast or slow the subject could perform a decision) and variable interdecision time, no dramatic change in the performance could be found.

23.5.4 Study 4: Asynchronous freeSpace Experiments

Our first paradigm designed to train and evaluate asynchronous control was called the "freeSpace virtual park" (see figure 23.4a). The VE consisted of hedges, a tree, and three coins to collect. The subject was sitting in front of a stereoscopic projection wall and wearing shutter glasses.

The aim of the paradigm was to explore the VE and collect the scattered items. Turn left and right and move forward were the navigation commands used to move through the freeSpace (IC). Whenever an IC command was detected by the BCI, the corresponding command was sent to the VE. When no IC pattern was detected (noncontrol state, NC) accordingly no navigation was performed. By using this simple navigation strategy, each corner of the VE was accessible. To realize this navigation, however, it was necessary to detect three different motor imagery–modulated brain patterns in the ongoing EEG. For more details on the setup of recordings and signal processing, see chapter 4.4.3 and Scherer et al. (Submitted).

Figure 23.4a shows a picture taken during a feedback experiment. In the lower part of the screen feedback arrows were displayed, indicating the actual navigation command. Figure 23.4b shows the bird's view map of the freeSpace park. The dark line illustrates the selected pathway of the subject. The starting point is marked with an "x" and the light grey circles indicate the items to collect. The collection starts each time the path intersects with an item, marked with a small dark circle. Additionally, the map shows that an infinite number of ways to collect the three items exist. The selected path, however, is dependent on the will of the subject only. For comparison, the corresponding BCI classification output (navigation) sequence is shown in figure 23.4c. The items were collected at time points (t), 40, 72, and 182 s (vertical line). By using this command sequence it is possible to reconstruct the pathway. With 36 percent, as required by the paradigm, the moving forward command had the highest frequencies of occurrence (f_{OCC}). With 26 and 24 percent, left and right turn were balanced. NC was detected in 13 percent of the cases (see figure 23.4d).

Although the NC at the actual stage was not explicitly tested and evaluated, high classification accuracy was very important for the motivation of the subjects. Since each run lasted several minutes, it was difficult to keep the concentration and therefore periods of NC were required. If NC was not properly detected, navigation commands were sent to the freeSpace and this was extremely frustrating for subjects.

23.6 Discussion and Conclusion

The presented studies describe the possibility and feasibility of using a motor imagery–based BCI with VR as feedback medium. Similar results in different virtual worlds with different types of motor imageries (left-hand, right-hand, and foot movement imagination) could be achieved but no significant differences in the BCI performance were observed between VR and non-VR feedback.

At this time it is unknown whether the feedback in form of a realistic VE can improve the BCI performance or not. However, there is strong evidence that observation of moving

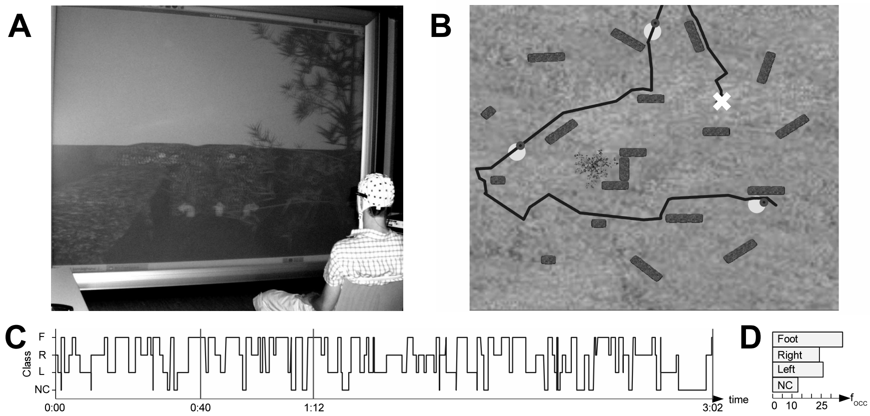

Figure 23.4 (a) Picture of the freeSpace VR experiments. (b) Bird's view of the park with the selected pathway (dark line), items to collect (light grey circle), pick-up position (small dark circle), and starting point (x). (c) BCI navigation command sequence. To operate the BCI, left hand (L), right hand (R), and foot (F) motor imagery were used. Also the noncontrol state (NC) was detected. The marked time (vertical lines) indicates the pick-up time. (d) The histogram on the right shows the frequency of occurrence for each class.

body parts can modify the sensorimotor activity (Pfurtscheller et al. (In press); Rizzolatti et al. (2001)), whereas observations of non-body parts have less influence on the brain activity (Altschuller et al. (2000)). With the coupling of BCI and VR a new research tool is available for investigating different research questions, for example, the impact of VR feedback to shorten the training time. Nevertheless, VR provides an excellent training and testing environment for procedures that may apply later in reality. One important application might be the use of VE for people with severe motor disabilities. If it can be shown that within VE people can learn to control their movements through space, the much greater expense of building physical devices (e.g., neuroprosthesis or a robotic arm) controlled by a BCI will be justified. One goal could be to move with a wheelchair through a virtual environment and afterward through the real world solely by the imagination of movements.

It must be noted, however, that in some experiments with VR feedback the task of the subjects was more challenging than in the experiments with the standard BCI feedback. In the presented experiments, all subjects achieved their best results within the VEs (either HMD or Cave) and the worst results in the standard BCI conditions. One possible interpretation is that VR feedback amplifies both positive and negative feedback effects on the performance: Generally, good performance is enhanced, but if the performance is not satisfactory, the VR feedback distracts and leads to higher frustration compared to the standard BCI feedback. Nevertheless, the use of VR stimulated the subject's performances and provided motivation.

High classification accuracy (low error rate) can be achieved only when the subjects correctly perform the indicated mental task. This not only requires focused attention to the corresponding body part, but also a withdrawal of attention from other body parts.

Because one run lasts several minutes, the subject must be vigilant the whole time, that is, concentrate on the task, anticipate and process the cue stimuli, and perform the indicated imagery task. This high mental load during each run and the performance of three to four consecutive runs within one recording (approximately 1 hour including electrode montage) can lead to a temporary drop in attention and an increased rate of misclassifications and errors. Presenting such an erroneous feedback to the subject can modify the EEG activity and result in a further deterioration of performance. Therefore, it is not surprising that in nearly all sessions and different conditions individual runs with inferior and superior performance were found (see figure 23.1d–f and 23.2d–f).

Concerning the difference between Cave, HMD and desktop PC experiments, the following observations are of interest:

(1) Subjects felt more natural in VE compared with BCI experiments with standard feedback.
(2) Each subject preferred the Cave experiments to the HMD and both were favored over BCI session on a desktop PC.
(3) Motivation (e.g., to "walk from thought" in a virtual street) seems to improve the BCI performance, but too much excitement might also distract the subject.
(4) Despite distraction from auditory and moving visual stimuli in VE, motor imagery and its classification in the ongoing EEG is still possible.

The research reported in this work is a further step to the long-range vision for interaction in multisensory environments exploiting mental-only activity.

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Notes

E-mail for correspondence: robert.leeb@tugraz.at