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Research Report

Walking from thought

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ARTICLE INFO

Article history:
Accepted 29 November 2005
Available online 10 January 2006

Keywords:
Motor imagery
Electroencephalogram (EEG)
Virtual reality (VR)
Event-related desynchronization (ERD)
Event-related synchronization (ERS)
Brain–computer interface (BCI)

ABSTRACT

Online analysis and classification of single electroencephalogram (EEG) trials during motor imagery were used for navigation in the virtual environment (VE). The EEG was recorded bipolarly with electrode placement over the hand and foot representation areas. The aim of the study was to demonstrate for the first time that it is possible to move through a virtual street without muscular activity when the participant only imagines feet movements. This is achieved by exploiting a brain–computer interface (BCI) which transforms thought-modulated EEG signals into an output signal that controls events within the VE. The experiments were carried out in an immersive projection environment, commonly referred to as a "Cave" (Cruz-Neira, C., Sandin, D.J., DeFanti, T.A., Surround-screen projection-based virtual reality: the design and implementation of the CAVE. Proceedings of the 20th annual conference on Computer graphics and interactive techniques, ACM Press, 1993, pp. 135–142) where participants were able to move through a virtual street by foot imagery only. Prior to the final experiments in the Cave, the participants underwent an extensive BCI training.

1. Introduction

A relatively recent development is called EEG-based brain–computer interface (BCI). By means of a BCI, specific features extracted from EEG signals are used, e.g. to operate devices and assist people with comprised motor functions (Wolpaw et al., 2002) or to control events in the virtual environment (VE) (Bayliss and Ballard, 2000; Leeb et al., 2004). In general, VE provides an excellent tool to test procedures which might be applied subsequently in reality, e.g. for patients with disabilities. If it is possible to show that people can learn to control their movements through space within a VE, it would justify the much bigger expense of building physical devices like, e.g. a robot arm controlled by a BCI. Another application of combining BCI and virtual reality technologies is using VE as feedback medium with the goal to enhance classification accuracy and shorten the time needed for BCI training sessions, e.g. to re-establish a communication channel in patients who are totally paralyzed (or "locked-in") (Pfurtscheller et al., 2005; Wolpaw et al., 2002).

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doi:10.1016/j.brainres.2005.11.083

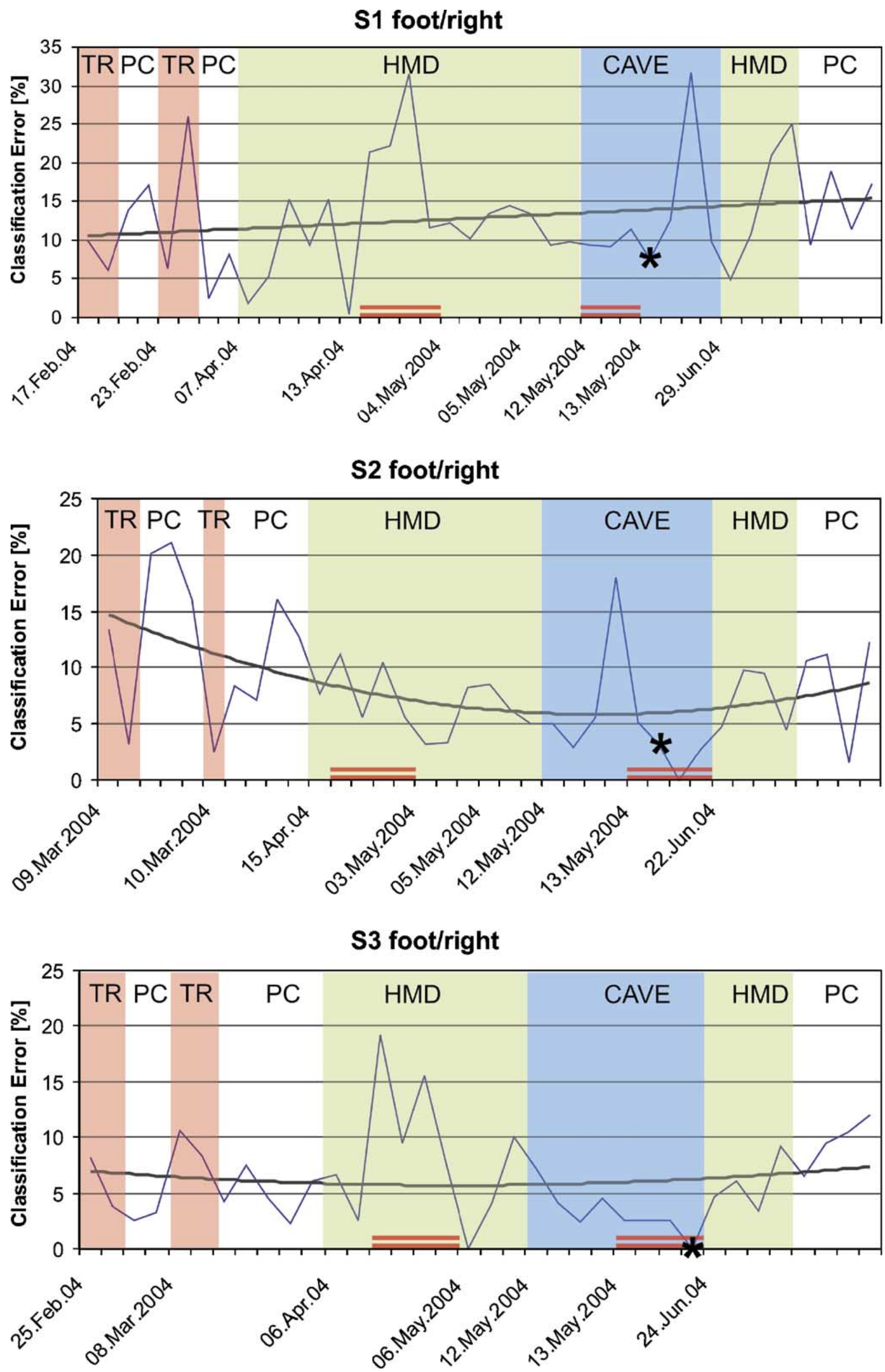

Fig. 1 – Classification error in percent (%) for all runs of the 3 subjects (S1, S2, S3). The runs with PC-FB, HMD-FB and Cave-FB and the training runs without FB (TR) are indicated in each subject. An interpolation of 2nd order has been performed to show the trend of the classification error over the 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. The two horizontal lines indicated the runs which have been used for calculation of the time–frequency maps in Figs. 2 and 3. The online performances of the runs marked with an "*" are displayed in Fig. 4.

One of the first who combined virtual reality (VR) and BCI technologies were Bayliss and Ballard (2000) using the P300 evoked potential components in combination with a head-mounted display (HMD)-based VR system. Subjects were instructed to drive a modified go-car in a virtual tour and stop at red lights while ignoring both green and yellow lights. The red lights were made to be rare enough to make the P300 suitable (Donchin et al., 2000). In this type of BCI the subject has to focus attention to the visual cue and obtain visual feedback when the goal was achieved.

Besides focused visual attention, motor imagery is also a suitable mental strategy in BCI research. In motor imagery, the participants do not have to focus on a certain flashing object in the VE but do have to imagine a specific motor act such as hand, foot or tongue movement. Motor imagery results in a somatotopic activation pattern, similar to the same physical movement being executed (Porro et al., 1996). In particular, hand and feet motor imagery affects sensorimotor EEG rhythms in a way that allows a BCI to generate a control signal of high reliability.

The goal of this paper is (i) to demonstrate that it is possible to move through a virtual street without any muscular activity, when the participant only *imagines* the movement of both feet; (ii) to investigate whether feedback in a BCI experiment in form of a moving scene in VE disturbs or motivates the participants.

Three able-bodied subjects firstly underwent a basic BCI training where a computer monitor was used for feedback (FB). Thereafter, advanced training was performed within a VE delivered on a head-mounted display (HMD), and finally a

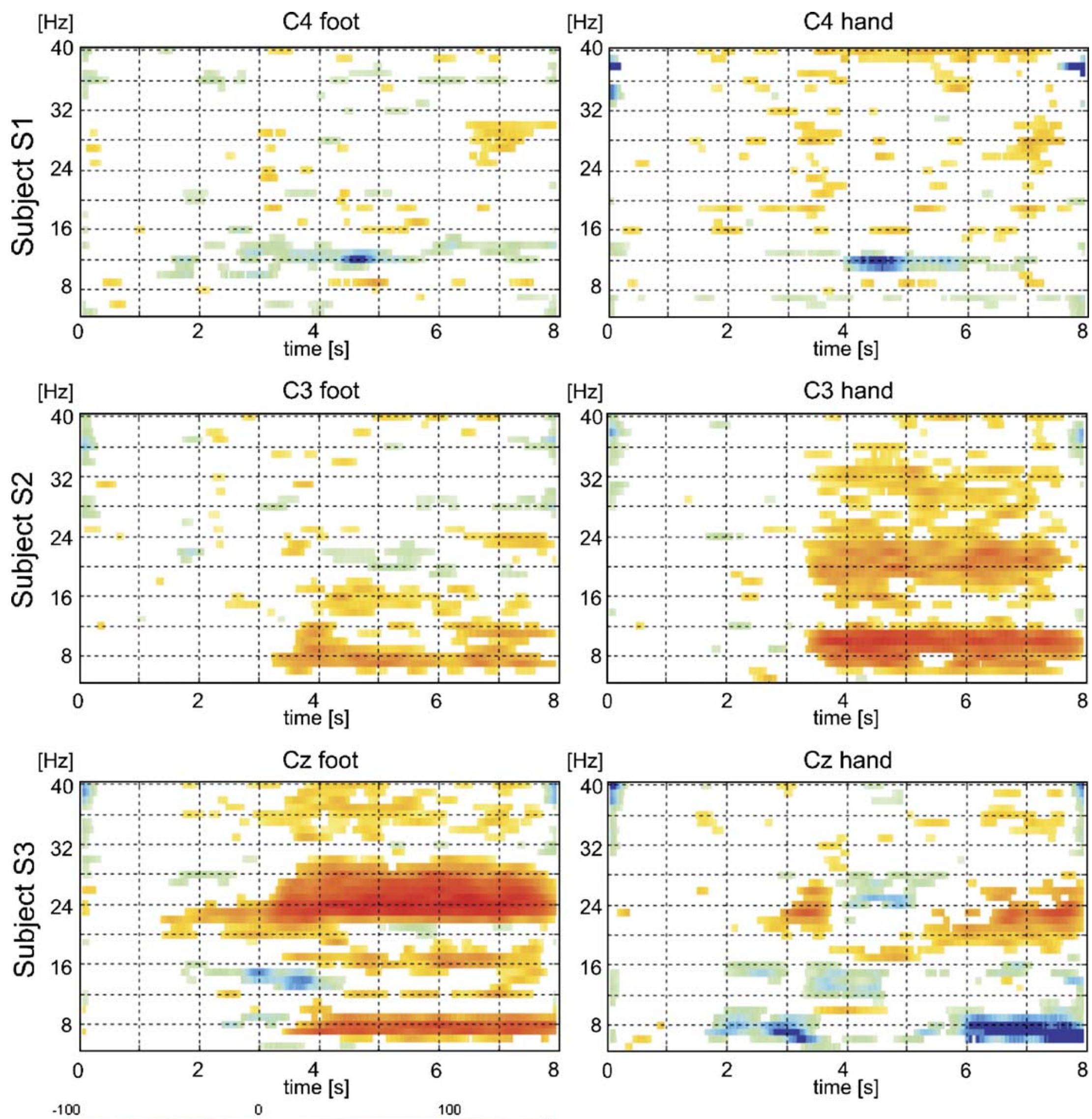

Fig. 2 – Selected time–frequency maps for different EEG channels and imagery tasks from subjects S1, S2 and S3 during the first HMD experiments (the four runs used for the calculation of these maps are indicated with two horizontal lines in Fig. 1). On the left side, the maps for feet imagery, and, on the right side, the appropriate maps for right hand imagery are displayed. The selected channels are different for each subject. "Blue" indicates areas with significant (P < 0.05) band power increase (ERS) compared with the reference period (second 0.5 to 1.5), and significant band power decrease (ERD) is indicated in "red". The cue stimulus was presented at second 3.

"walking" task was carried out in the ReaCTor, a Cave-like system (Cruz-Neira et al., 1993) at University College London (UCL).

2. Results

2.1. Classification accuracy over runs

After the experiment the online classification output of the LDA of each run was analyzed. Furthermore, the best (lowest) classification error within the feedback time of a trial (between second 4.25 and 8) was used as classification error of this run. In case of training runs without FB, the classification error time course was calculated offline.

The classification error of all runs without and with FB over a period of 5 months is displayed in Fig. 1. The runs with PC, HMD and Cave are separately indicated. Altogether subject S1 performed 4 TR runs, 8 runs with PC, 21 runs with HMD and 7 runs with Cave FB. Subject S2 performed 3 TR runs, 11 runs with PC, 15 runs with HMD and 8 runs with Cave FB and finally subject S3 performed 4 TR runs, 11 runs with PC, 13 runs with HMD and 8 runs with Cave FB. The time courses of the classification error of the individual subjects fluctuated considerably over runs and displayed slightly different trends in the 3 subjects.

Surprisingly, the error rate displayed a decreasing trend only in subject S2. In subject S3, the error rate kept nearly constant on the 7% level, and, in subject S1, the error rate showed an increasing tendency. In the control experiment after the Cave condition, a slightly increased error rate was found in all 3 subjects. The relatively constant and low error rate of subject S3 can be explained by the observation that, if somebody has established a specific EEG pattern associated with motor imagery in the course of many BCI training sessions, this pattern can display a long-term stability. For

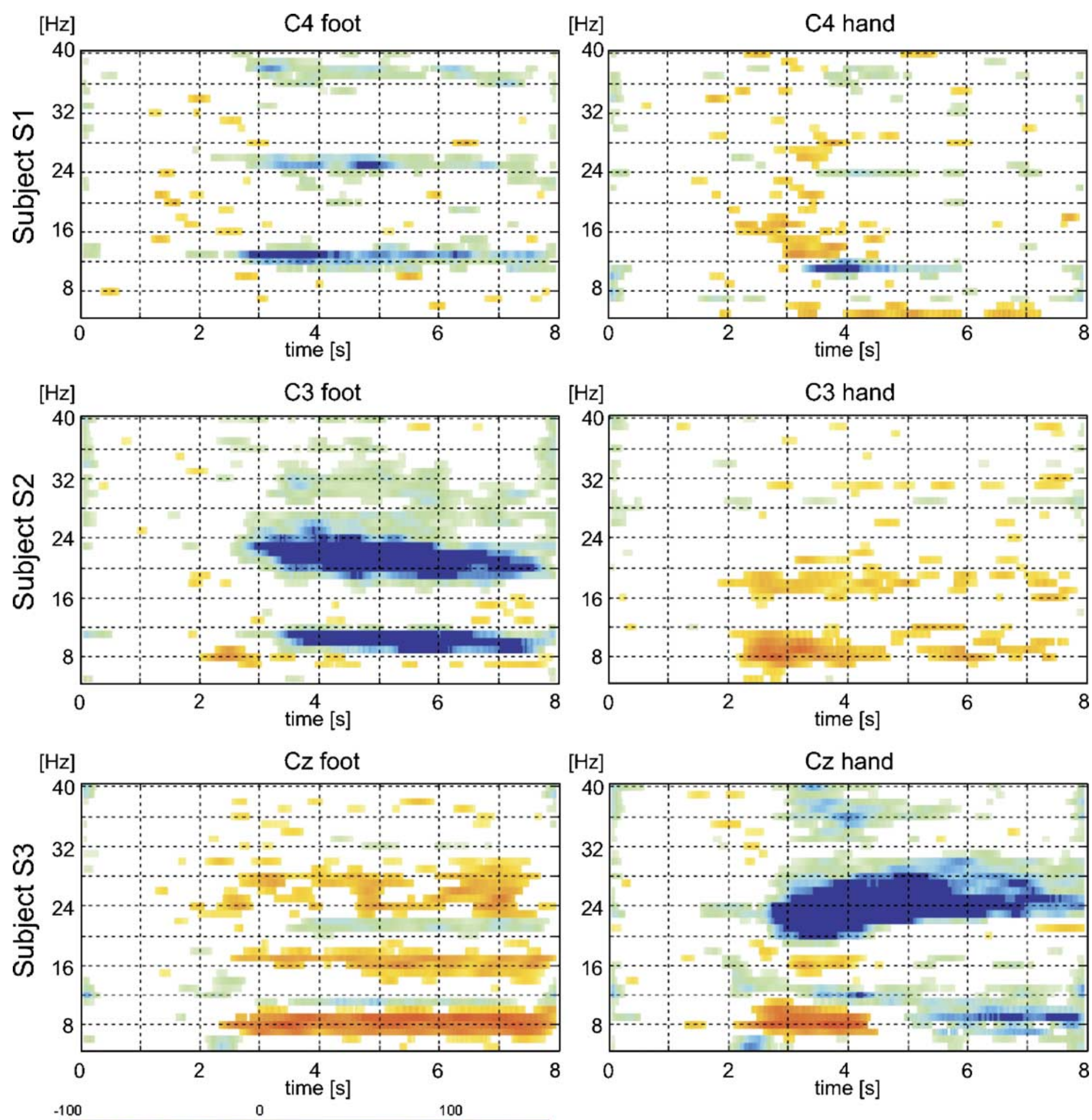

Fig. 3 – Selected time–frequency maps from subjects S1, S2 and S3 during the Cave experiments. The same channels as in Fig. 2 are used, and the used runs are marked in Fig. 1. For further explanation, see Fig. 2.

example, one of our subjects induced mentally large trains of beta oscillations after 4 months of training (Pfurtscheller et al., 2005). This subject was able to generate the same EEG pattern after many years despite long pauses of several months between the BCI sessions.

2.2. EEG patterns

It is of interest which type of EEG pattern is associated with poor or good classification accuracy (minimal classification error) during the experiments. For demonstration purposes, we selected 2 time–frequency maps from one specific EEG channel in each subject to show the dynamic behavior of brain oscillations during hand and foot motor imagery (see Figs. 2 and 3). The "red color" in each map marks a significant power (amplitude) decrease or event-related desynchronization (ERD) and the "blue color" a significant power (amplitude) increase or event-related synchronization (ERS) of the corresponding frequency component. The data of one HMD session (Fig. 2) and one Cave session (Fig. 3) have been analyzed offline. In this analysis, the trials with artefacts were excluded, whereby in one run with 40 trials between zero to four artefacts had been found through a manual inspection.

Characteristic for all 3 subjects in the Cave condition is a dominant ERS pattern which was permanently present (see Fig. 3). In subject S1, the 12-Hz and 24-Hz components (characteristic of the arch-shaped mu rhythm) were enhanced during foot motor imagery in channel C4. Similarly, in subject S2, the 11-Hz and 22-Hz components were enlarged during motor imagery in channel C3. In contrast, however, in subject S3, the 24-Hz component was enhanced during hand motor imagery in channel Cz. In summary, it can be stated that feet motor imagery synchronized and induced brain oscillations in the hand representation area (channels C3 and C4 in subjects S1, S2) and hand motor imagery in the foot representation area (channel Cz in subject S3). In contrast to the Cave condition (Fig. 3), the maps calculated in the HMD condition (Fig. 2) displayed less pronounced ERS pattern.

2.3. Walking distance in the Cave

Online "Cave results" from one run during the second session in the Cave (indicated by "*" in Fig. 1) are displayed in Fig. 4 for all subjects. Subject S3 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 a CAM of 0%.

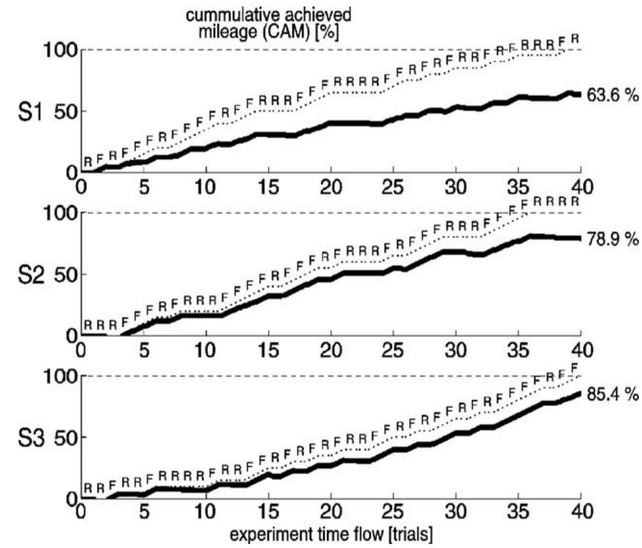

Fig. 4 – Online performance measures from one run (indicated with an "*" in Fig. 1) obtained in all 3 subjects (S1, S2 and S3). Besides the theoretical possible CAM (dashed line), also the real CAM (full line) is displayed. The "cumulative achieved mileage" (CAM) is the summed up distance which was walked forward during foot motor imagery. The theoretical possible CAM would be the perfect performance, therefore a correct classification would be necessary during the whole feedback time over all trials within one run. 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. Consequently, the maximum possible CAM is limited to 100%, and the real achieved is 63.6% for subject S1, 78.9% for S2 and 85.4% for S3.

3. Discussion and conclusion

Combining BCI and virtual reality technologies may provide the possibility to realize a "natural" interface for navigation of a VE. As an important step in this direction, the data reported show that EEG recording and single trial processing are possible in a Cave-like system and that the obtained signals are even suitable to control events within a VE in real time. Furthermore, the present study revealed that motor imagery is an adequate mental strategy to control actions or events within the VE. However, it is important that each subject goes through a number of training runs or sessions with the goal to set-up a subject-specific classifier able to discriminate online and in real-time between two mental states.

High classification accuracy (low error rate) can only be achieved, when the subjects perform correctly the indicated mental task. This does not need focused attention to the corresponding body part only, but also to withdraw attention from other body parts. Because one run lasts about some minutes, the subject has to be aware the whole time, 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 3–4 consecutive runs within one session (approximately 1 h, including montage) can lead to a temporal drop of attention and resulting in misclassification and errors. Such an error indicated to the subject by visual feedback can modify the EEG activity and results in a further deterioration of the performance. Therefore, it is not surprising that in nearly all sessions and different conditions individual runs with inferior classification accuracy exist (see Fig. 1, e.g. HMD conditions in subject S1 and S3 or Cave condition in subjects S2 and S3). However, there are always single runs with a superior performance in each condition (see e.g. runs with an error rate close to zero in subjects S1, S2 and S3).

One reason for these inferior classification results of individual runs with subjects S1 and S2 during the Cave condition (classification error of 32% in S1 and 18% in S2) could be the loss of concentration in connection with a moving visual scene. This visual scene did not only consist of a street with houses and shops, but also of moving characters. In this case, interference between the motor imagery task and the observation of moving objects can be expected. This might be due to the fact that not only motor imagery can have an impact on neurons in motor areas, but also observation of moving objects (Rizzolatti et al., 2001).

A prerequisite for a successful online discrimination between hand and foot motor imagery based on 3 EEG channels is the ability of a subject to induce both ERD and ERS (Pfurtscheller and Lopes da Silva, 1999) at the same moment of time. Examples of such patterns are shown in Fig. 3.

An interesting question is how the imagery-induced brain oscillations (ERS) in the hand or foot representation areas can be explained. Basically, hand motor imagery activates the cortical hand representation area in the crown of the precentral gyrus which is manifested as desynchronization of central mu and beta rhythms (hand area ERD). Less clear is the activation of the foot representation area during foot motor imagery because of its location in the mesial brain surface, where potentials are not easily accessible to EEG electrodes. It is important that, after feedback training, feet motor imagery is not only accompanied by a more or less weak foot area ERD, but also by a dominant hand area ERS (see Fig. 3, subjects S1 and S2). Analogically, also hand motor imagery can be accompanied by a foot area ERS (Fig. 3, subject S3). While the ERD can be seen as a correlate of an activated neural network, the ERS, at least under certain circumstances, can be interpreted as a correlate of a deactivated or even inhibited network (Pfurtscheller and Lopes da Silva, 1999). Hand motor imagery activates the hand representation area and can deactivate (inhibit) the foot representation area (example subject S3 in Fig. 3), and foot motor imagery activates the foot representation area inside the sulcus of gyrus or somewhere in between and can simultaneously deactivate (inhibit) the hand representation area (examples S1 and S2 in Fig. 3). This interaction between different anatomically distinct cortical areas can be found within the same modality (e.g. different body parts) but also between different modalities (e.g. motor vs. visual processing). Furthermore, this interaction can be interpreted as a mechanism for increasing the neural efficiency and optimizing the mental strategy. PET and fMRI investigations serve as a good support for the observation of a focal activation together with a simultaneous inhibition of distant cortical areas. A decrease of blood flow in primary somatosensory areas was observed, when the subject attended to tasks involving non-tactile modalities (intermodal interaction) (Kawashima et al., 1995). A similar decrease in blood flow arises in the somatosensory cortical representation area of one body part, whenever attention is divided to a distant different body part (intramodal interaction) (Drevets et al., 1995). Evidence from fMRI studies in the visual system also shows that attention directed to one stimulus counteracts competitive suppression from multiple visual stimuli in nearby visual space (Kastner et al., 1998).

All these observations suggest that information processing in a task-essential cortical area is enhanced relative to depressed (inhibited) processing in non-essential areas. It is very likely that neural networks can be shaped by training with feedback in the form that networks in non-essential areas become increasingly deactivated (inhibited) relative to activated networks. This shaping process may be responsible for the synchronization of the hand area mu rhythm during feet motor imagery and the synchronization of the foot area beta rhythm during hand motor imagery, respectively.

Concerning the difference between Cave, HMD and desktop PC experiments, no statistical evaluation of the data was possible. Nevertheless, the following observations are of interest for future research:

(i) subjects felt more natural in VE compared to BCI experiments with desktop PC
(ii) all subjects liked the Cave experiments more than the HMD, and both were much preferred over BCI session on a desktop PC
(iii) motivation to "walk through thought" in a virtual street seems to improve the BCI performance, but too much excitement might also distract the subject.
(iv) despite watching movements in VE, motor imagery and its classification in the ongoing EEG are still possible.

In further studies, it will be of critical importance to change the experimental paradigm as to eliminate externally paced cues. In this way, the participant could decide to start walking at will. Such an uncued or asynchronous BCI system (Pfurtscheller et al., 2005) is, however, more demanding and only leads to satisfactory classification results when the user is able to induce marked ERS patterns by motor imagery (Pfurtscheller et al., in press) and when false positive classifications are minimized during resting or idling periods.

The research reported represents a crucial step to the long-range vision of multi-sensory 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 2 mental states have to be classified (Pfurtscheller et al., 2005; Scherer et al., 2004; Wolpaw et al., 2002). An alternative is to use direct implants into the brain for computer control, as discussed recently by Nicolelis (2001). In this case, we have an excellent signal-to-noise ratio and can classify more than 2 mental states with high accuracy but are confronted with all the problems in connection with a highly invasive system.

4. Experimental procedures

4.1. *Subjects and EEG-recording*

The study was performed on three healthy volunteers aged 23, 28 and 30 years. All subjects were right-handed and without a history of neurological disease. They gave informal consent to participate in the study. The EEG was recorded bipolarly with electrodes placed 2.5 cm anterior and 2.5 cm posterior to position C3 (channel C3), position C4 (channel C4) and position Cz (channel Cz) of the international 10/20 system. The ground

Table 1 – Dependency between the predetermined cue classes and the movements imagined by the subject and their resulting motions performed in the virtual street

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

electrode was positioned on the forehead. The signals were recorded at a bandwidth of 0.5–30 Hz by means of an EEG amplifier (g.tec Guger Technologies, Graz, Austria). Real-time processing was performed with a sampling frequency of 250 Hz under Matlab 6.5 and Simulink 5.0 (The MathWorks, Inc., Natick, USA) using rtsBCI (Scherer, available online) and the open source package BIOSIG (Schloegl, available online). No online artefact detection was used. For offline processing, all trials were visually controlled for artefacts and affected trials were excluded from further analyses.

4.2. *Signal processing*

For online classification, two frequency bands (logarithmic band power, BP) obtained from the three EEG channels were used. These features were classified with Fishers linear discriminant analysis (LDA, Bishop et al., 1995) and transformed into a control signal (for details, see Leeb et al., 2004; Pfurtscheller et al., 2003). The output of the classifier was either used to control the length and orientation of a bar (PC condition, see Section 4.3) or to move through a virtual street (HMD or CAVE condition, see Sections 4.4 and 4.5, respectively).

In the offline evaluation, the EEG data were analyzed with an ERD/ERS (event-related (de)-synchronization) procedure (Graimann et al., 2002). The ERD/ERS time–frequency maps were calculated for purpose of convenient data inspection. Each map displays significant ($P > 0.05$, bootstrap algorithm) band power changes within a frequency range of 6–40 Hz[1] with a frequency resolution of 1 Hz and frequency bands of 2 Hz. Only artefact corrected trials were used for ERD/ERS map calculation (examples are illustrated in Figs. 2 and 3).

4.3. *Basic BCI training*

All three subjects already had BCI experience at the beginning of the study (Pfurtscheller et al., 2003). Nevertheless, a number of training runs were performed with the goal to obtain a low and stable classification error. In general, all daily runs defined one session (between 3 and 8 runs). In each run, the subject had to imagine feet or right hand movement in response to an auditory cue stimulus in form of a single beep (hand imagery) or double beep (feet imagery). Each run consisted of 40 trials (20 feet-cues and 20 right hand-cues), and the sequence of the cues was randomized within each run. The subjects were instructed to imagine moving softly both feet or imagine clutching softly a ball with their right hands while they were sitting in a comfortable arm chair and rested their arms relaxed on the armrest. Subjects were asked to imagine kinesthetic experience of movements while avoiding muscle tension. Additionally during the training runs (TR), a visual cue was presented on a computer monitor like in the standard Graz-BCI paradigm (Pfurtscheller et al., 2003) as an arrow pointing downwards or to the right, respectively. Each trial started with a fixation cross (second 0) followed by the cue stimulus at second 3 (the visual cue was presented for 1.25 s). The intervals between trials were randomized in the range from 0.5 to 2 s. Twenty EEG trials of 8 s duration for every imagery task were recorded bipolarly in one run.

The EEG trials from the first two runs of the first session without FB (marked with TR in Fig. 1) were used to set up a classifier able to discriminate between the two different mental states. For this initial classifier, standard frequency bands have been used (10–12 Hz and 16–20 Hz). In further runs, visual FB in the form of a moving bar was given to inform the participant about the accuracy of the classification during each imagery task (that is, classification of right hand imagery was represented by the bar moving to the right, classification of foot movement imagery was illustrated by the bar moving downward).

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 Genetic Algorithm (Goldberg et al., 1989; Scherer et al., 2004). The purpose of the optimization task was to find two BP features for each channel, with two non-overlapping frequency bands best suitable to discriminate between both mental tasks. The optimized frequency bands were for subject S1 11–16 Hz and 22–26 Hz, for subject S2 10–15 Hz and 20–27 Hz and for subject S3 10–16 Hz and 19–27 Hz. For these optimized frequency bands, a new classifier was calculated and used in all the remaining sessions, independently of the conditions.

4.4. *Advanced training with a HMD*

After the basic training with simple FB on a computer monitor, the training procedures as described above were repeated with a 3-dimensional FB using a V8-HMD (Virtual Research Systems, Inc. Aptos, USA). Correct classification of feet motor imagery was accompanied by moving forward with constant speed in the projected virtual street. The task of the subject was to walk to the end of the street, provided that the appropriate cue was given (see Table 1). Correct classification of hand motor imagery allowed the

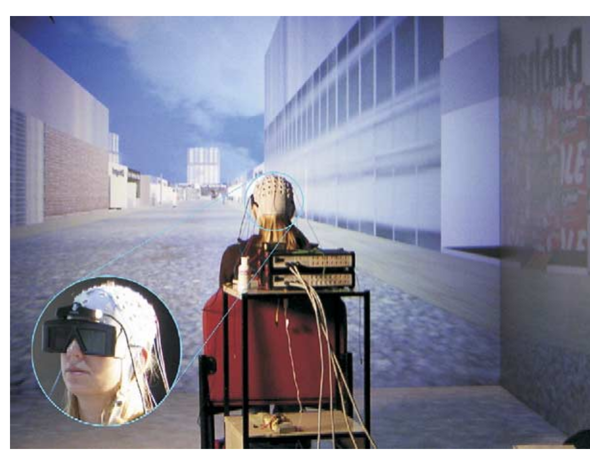

Fig. 5 – Picture of one participant during the experiment in the ReaCTor/Cave. In the background of the picture, the virtual street with shops and animated avatars is projected in stereo view so that the participant has the illusion of being in the street. In reality, the subject is sitting on a comfortable chair, wearing shutter glasses and an electrode cap (see zoomed picture).

[1] Because of the use of a low order analogue filter with a cut-off frequency of 30 Hz (order 2 with an attenuation of 40 dB), the time–frequency maps are calculated up to 40 Hz. The information in the upper range of the frequency map is not used for the implemented BCI, but as a quality measure for the signals.

subject to remain stationary. Incorrect classification of feet motor imagery also resulted in halting motion and incorrect classification of hand motor imagery in backward motion (see Table 1, Leeb et al., 2004). Each subject performed a number of runs organized in 3 to 4 sessions with the HMD.

4.5. BCI experiments in the Cave

Finally, the 3 able-bodied subjects were placed in the ReaCTor (SEOS Ltd., West Sussex, UK) at the UCL (Fig. 5). This is an example of a type of system commonly called a "Cave" (Cruz-Neira et al., 1993). It surrounds participants by three back-projected active stereo screens (3 walls) and a front-projected screen on the floor. A special feature of any Cave 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. The subject was sitting on a chair in the middle of the Cave and was connected to the same regular EEG amplifier (see Fig. 5).

The same experimental protocol as for the experiments with the HMD was used. The walking distance was scored as a "cumulative achieved mileage" (CAM). The CAM is the accumulated forward distance which was covered during feet motor imagery and is used as a performance measure.

Altogether, 40 cue stimuli (single beep for right hand motor imagery and double beep for feet motor imagery) were presented in random order. For each run, two different CAMs can be computed. One is the real performed CAM, and the other one is the theoretical possible CAM. The theoretical CAM would be ideally possible performance, so a correct classification must happen over the whole feedback time of all trials. The variation of this ideal pathway in Fig. 4 is caused by the randomization of the sequence of the 20 foot and 20 right hand movements through each run to avoid adaptation, but the maximum achievable mileage is always the same.

4.6. Control experiments after the Cave condition

After the Cave experiments one control session (4 runs) under the HMD condition and one control session under the PC condition were performed. These additional sessions have been conducted to investigate possible performance changes caused by the different conditions or influenced by training.

Acknowledgments

The work was funded by the European PRESENCIA project (IST-2001-37927). Thanks to Vinoba Vinayagamoorthy and Marco Gillies for allowing the use of the street scene virtual environment and special thanks to Jörg Biedermann, Gernot Supp and Doris Zimmermann for their participation.

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