Walking from thoughts: Not the muscles are crucial, but the brain waves!

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Abstract

Able-bodied participants are able to move forward in a Virtual Environment (VE) by imagining movements of their feet. 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" in which participants were able to move through a virtual street by foot imagery alone. Experiments of BCI feedback on a normal monitor, VE experiments with a head-mounted display (HMD) and in the Cave-VE are compared.

Keywords — ***Virtual environment (VE), Brain-Computer Interface (BCI), walking, thoughts***

1. Introduction

"Yes he was walking! The illusion was utterly convincing …" experienced the leading actor from Arthur C. Clark in the book 3001, the final odyssey [1], when he was wearing a "Braincap" connected to the "Brainbox". Thereby he could experience this science fiction technology and explore different virtual and ancient real worlds. Has this dream gone real? Here we show that participants are able to move forward – "to walk" – in a Virtual Environment (VE) by imagining movements of their feet.

The improvement of seamless and natural human-computer interfaces is an all-the-time necessary task in virtual reality (VR) development. An interesting research problem is to realize locomotion through a VE only by mental activity or "thought". Typically, participants navigate by using a hand-held device, such as a joystick or a wand. Unfortunately contradictory stimuli appear in such situations; on the one hand the world around them is moving, which generates the illusion of walking, but on the other hand the participant is thinking on his index finger, for pressing the button on the joystick. This results in a reduced sense of being present in the VE, and is one of the causes of simulation sickness [2].

A possible next step towards next-generation interfaces could be achieved by exploiting a Brain-Computer Interface (BCI) which represents a direct connection between the human brain and the computer [3]. The electroencephalogram (EEG) of the human brain encompasses different types of oscillatory activities, in which the oscillations in the alpha and beta band (event-related desynchronization, ERD [4]) are particularly important to discriminate between different brain states (e.g. imagination of movements). A BCI transforms thought-modulated EEG signals into an output signal [3] that can control events within that VE [5, 6].

The goal of this work is to demonstrate that it is possible to move through different VEs, e.g. a virtual street, without any muscular activity, when the participant only imagines the movement of both feet and to show the influences of different feedback modalities on the same task.

VR provides an excellent testing ground for procedures that may apply later in reality. One important future application may the use of VE for people 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 as e.g. a robot arm controlled by a BCI.

2. Methods

2.1. Graz Brain-Computer Interface

Direct Brain-Computer communication is a novel approach to develop an additional communication channel for human-machine interaction. The imagination of different types of movements, e.g. right hand, left hand, foot or tongue movement, results in a characteristic change of the EEG over the sensorimotor cortex of a participant [4].

The Graz-BCI detects changes in the ongoing EEG during the imagination of hand or foot movements and transforms them into a control signal [7]. Three bipolar derivations, located 2.5 cm anterior and posterior to the electrode positions C3, Cz and C4 of the international 10/20 system [8] were recorded with a sampling frequency of 250 Hz (sensitivity was set to 50µV) and bandpass filtered between 0.5 and 30 Hz. The ground electrode was positioned on the forehead.

The logarithmic bandpower (BP) was calculated for each channel by digitally band-pass filtering the EEG (using a Butterworth filter of order 5) in the upper alpha (10 - 12 Hz) and beta band (16 - 24 Hz), squaring the signal and averaging the samples over a 1-s epoch. The resulting 4 BP features were transformed with Fishers linear discriminant analysis (LDA) [9] into a control signal. Finally the computed control signal was used to control / modify the feedback (FB) and either visualized on the same PC as a bar (see Figure 1a) or sent to the VE as a steering input inside a virtual world (see Figure 1b and 1c) [5].

The complete biosignal analysis system consisted of an EEG amplifier (g.tec, Graz, Austria), a data acquisition card (National Instruments Corporation, Austin, USA) and a recording device running under WindowsXP (Microsoft Corporation, Redmond, USA) on a commercial desktop PC [10]. The BCI algorithms were implemented in MATLAB 6.5 and Simulink 5.0 (The MathWorks, Inc., Natick, USA) using rtsBCI [11] and the open source package BIOSIG [12].

Detailed information about the physiological background of motor imagery and ERD can be found elsewhere [4, 13], also about signal processing, feature extraction and the Graz-BCI [7, 10] and generally about various BCI systems [3, 14].

2.2. Participants and experimental paradigm

Three healthy participants (between 23 and 30 years) took part in these experiments over 5 months. All were right handed and without a history of neurological disease and gave informal consent to participate in the study.

In the first step a number of training runs (TR) were performed with each subject. These data were used to setup a classifier, which can be used in the next step for providing a feedback (FB) to the subject. The visual FB informs the participant about the accuracy of the classification during each imagery task.

The performances of three different FB conditions are compared: first the results of the standard BCI bar-FB with a simple bar (see Figure 1a), secondly using a head mounted display (HMD) as FB device (see Figure 1b) and finally using a highly immersive "Cave" projection environment (see Figure 1c).

Each feedback condition was measured multiple times (called sessions) and the order of recording was condition bar, HMD, Cave, HMD, bar. Figure 3 displays which type of FB has been used in each run and session, respectively. In each session 4 runs have been performed, whereby each run consisted of 40 trials (20 foot and 20 right-hand cues, in random order) based on the standard Graz-BCI paradigm [7]. Each trial lasts about 8 second and between the trials was a randomized interval in the range from 0.5 to 2 seconds. The data of the standard BCI run was used to compute a LDA classifier and the error rates were estimated by a 10 times 10-fold cross-validation LDA-training. The calculated classifier with the best classification accuracy during the imagination period (between second 4.5 and 8, in 0.5 s intervals) was selected for further use in all feedback runs. Further details of BCI training with motor imagery can be found elsewhere [7].

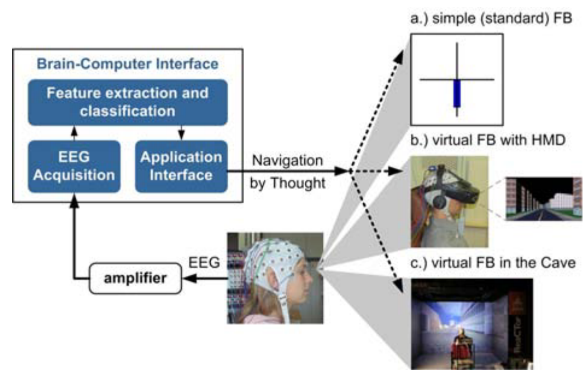

Figure 1: Schematic model of the used BCI-VR system with the participant wearing the electrode cap. Three different visual feedback modalities are displayed: (a) standard feedback whereby a vertical bar is controlled by the BCI output. (b) The participant is wearing a HMD. A screenshot of the virtual environment as seen by the participant is displayed at the far right. (c) Picture of one participant during the experiment in a Cave-like system. The surrounded projected environment creates the illusion of being in a virtual street. (b,c) Navigation through the VE is controlled by the output of the BCI.

2.3. Simple standard BCI feedback

In each run the participant had to imagine feet or right hand movement in response to a visual cue-stimulus presented on a computer monitor, in the form of an arrow pointing downwards or to the right, respectively. In addition to the visual cue an auditory cue stimulus was also given either as a single beep (hand imagery) or as double beeps (feet imagery). A visual feedback in the form of a moving bar (see Figure 1a) was given to inform the participant about the accuracy of the classification during each imagery task (i.e. classification of right hand imagery was represented by the bar moving to the right, classification of foot movement imagery made the bar moving downward).

2.4. Virtual feedback with a HMD

Virtual reality FB was presented with VRjuggler [15] and a Virtual Research V8 HMD (Virtual Research Systems, Inc., Aptos, USA) driven by an ATI Radeon 9700 graphics card (ATI Technologies, Inc., Markham, Canada). The given task of the participant was to walk to the end of the street inside this virtual city, whereby any time the computer identified the participant's brain pattern as a foot movement a motion happened (see Figure 1b). The same BCI paradigm as in the condition above (section 2.3) was applied, only the cue was given just acoustically. Correct classification of feet motor imagery was accompanied by moving forward with constant speed in the projected virtual street and the motion was stopped on correct classification of hand motor imagery (see Table 1). Incorrect classification of foot motor imagery resulted as well in halting, and incorrect classification of hand motor imagery in backward motion [16]. The walking distance was scored as a "cumulative achieved mileage" (CAM), which is the accumulated forward distance covered during feet movement imagination and is used as a performance measurement.

		subject imagined	
		foot movement	hand movement
Cue class	foot movement	forward	stop
	hand movement	backward	stop

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

2.5. Virtual feedback in the Cave

Two sessions were performed in London in a multi-projection based stereo and head-tracked VE system commonly known as a "Cave" [17]. The particular VE system used was a ReaCTor (SEOS Ltd.¸ West Sussex, UK) which surrounds the user with three back-projected active stereo screens (3 walls) and a front projected screen on the floor (see Figure 1c). Left- and right-eye images are alternately displayed at 45Hz each, and synchronized with CrystalEye™ stereo glasses. A special feature of any VE 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 [18]. The application implemented in DIVE [19] was a virtual main street with various shops on both sides (see Figure 2). Some of the shops could theoretically be visited but in this experiment the task was to go only straight forward as far as possible. The street was populated with some virtual characters that walked along the street, whereby the characters were programmed to avoid collisions with the participant. The communication between the BCI and the VR was done via the Virtual Reality Peripheral Network (VRPN, [20]).

Figure 2: Participant in the virtual main street with shops and animated avatars during the Cave-FB. The subject wears an electrode cap (connected to the amplifier) and shutter glasses.

3. Results

All participants were able to navigate in the different VE's and the achieved BCI performance in the VR tasks was comparable to standard BCI recordings. The usage of VR as FB was stimulating the participant's performances. Especially in the Cave condition (highest immersion) the performance of 2 participants was excellent (up to 100% BCI classification accuracy of single trials), although variability in the classification results between individual runs occurred (see Figure 3 and 7).

All runs performed consecutively on one day are called one session and most of the time one session contains four runs. In Figure 3 all performed runs over a period of 5 month with simple standard bar-FB, HMD-FB and Cave-FB and the trainings runs without FB (TR) are indicated in each subject. All runs following the indicated date are performed at this day. Each run consisted of 40 trials, 20 trials with a cue for foot imagery and 20 for right hand imagery in randomized order. The duration of a trial is 8 seconds (a random pause of 0.5 to 2 seconds is added between the trials to avoid adaptation), therefore a run lasted approximately 6.5 minutes and one session lasted about 1 hour including the time electrode montage.

Concerning the difference between the various feedback modalities no statistical evaluation of the data was possible, because only three individuals participated in these experiments.

The results are split into two parts: on the one hand the classification accuracy of the BCI is interesting to study the influence of the different FBs on the participants and on the other hand the task performances.

3.1. BCI classification

The BCI classification error is a measure how good the two brain states could be identified in each run. A classification error of 0 % denotes a perfect separation between the two mental tasks (20 examples for right hand movement imagination and 20 examples for foot movement imagination). A random classification would result in a classification error of 50 %. The error varies over the time of the trial (see Figure 4, the exemplarily used runs are indicated in Figure 3 with a black diamond). At second 3 the participant heard the cue (single or double beep) and started to imagine the desired movement. The optimal performance varies over the measurements and between individuals, but is typically at least two seconds after the trigger [21], see Figure 4 for the BCI classification of each participant of one run during the Cave experiments. Especially participant P3 could achieve a long and stable brain pattern over nearly the whole FB time (last row in Figure 4), which directly corresponds to very good CAM in Figure 5.

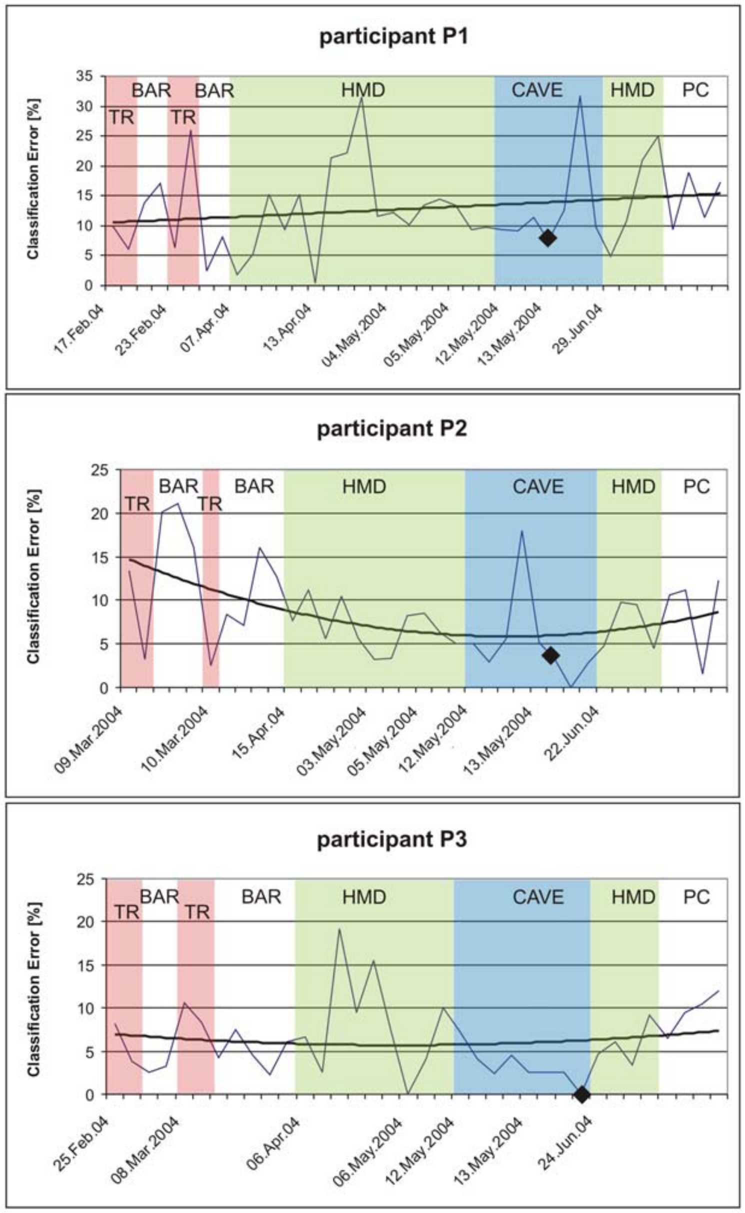

Figure 3: Classification error (in %) for all runs of the 3 participants. Runs with BAR-FB, HMD-FB and Cave-FB and the trainings rungs without FB (TR) are indicated in each subject. An interpolation of 2nd order shows the trend of the classification error over the time (black line). More than one run has been performed on each day, therefore all data points following the indicated date are performed at this day. The runs marked with a black diamond ▯ (one in each subject) are analyzed in detail in Fig. 3 (classification error) and in Fig. 5 (CAM, task performance).

The results of all runs with FB over a period of 5 months are displayed in Figure 3. Separately indicated are the runs with bar-FB, HMD-FB and Cave-FB. An interpolation of 2nd order has been performed to show the trend of the classification error over the time (thick black line). The time-courses of the classification error of the individual participants, on the one side, fluctuate considerably over runs and, on the other side, display different trends in the 3 participants: in participant P1 the classification error shows a slightly increasing trend over runs, in participant P2 a minimum during the Cave experiments and in participant P3 a relative constant level.

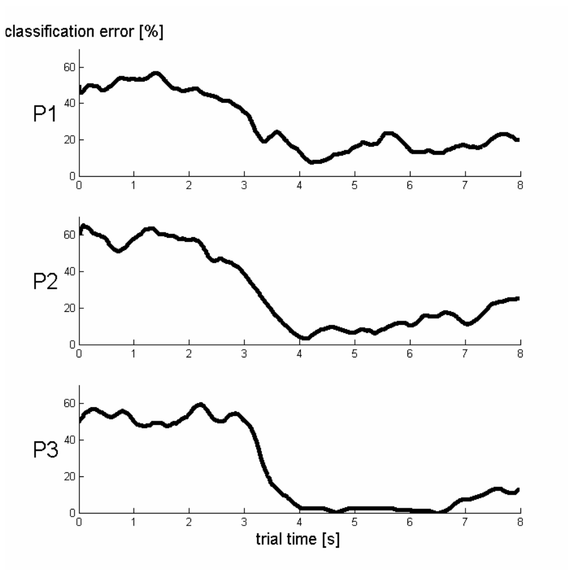

Figure 4: Mean classification error (in %) of one run (marked with a black diamond in Figure 3) over the trial time of all 3 participants. At second 3 the participant heard the cue (single or double beep) and started to imagine the specified movement during the FB period (between second 4.25 and 8).

3.2. Task performance

Some single run results of the first session with the Cave-FB obtained for the 3 participants are exemplary displayed in Figure 5 (this runs are indicated in Figure 3 with a black diamond and are the same runs as displayed in Figure 4). Both the theoretically possible CAM is plotted in dashed and the real achieved CAM as a full line. Because each participant had a different sequence of the 20 foot (F) and 20 right hand (R) motor imageries which were randomly distributed to avoid adaptation, the theoretical pathways are different in all pictures. Nevertheless the numbers of trials for both classes are the same and therefore the maximum possible CAM is the same. Participant P3 achieved the best performance with a CAM of 85.4 %. A CAM of 100 % corresponds to a correct classification of all 40 imagery tasks over the entire feedback time. A random classification would result in a CAM of 0 %. For comparison reasons the CAM performances of the bar-FB experiments have been simulated offline.

In Figure 6 the mean achieved CAM of all participants and condition is plotted. The trend of each participant over the FB conditions is plotted as grey dashed line. Figure 7 displays a detailed analysis of the same data. Each box plot has lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of the box to show the extent of the rest of the performances. The trend of each participant over the three FB conditions is indicated with a grey dashed line. Two participants' show an increase over the condition, but participant P1 achieved worse results with the HMD.

It is nearly impossible to achieve the maximum gain able CAM of 100%, because every small procrastination or hesitation of the participant results in reduced mileage. For a perfect outcome, a correct classification must happen during the whole FB time of all trials. Therefore the results are not directly comparable to normal BCI performance results.

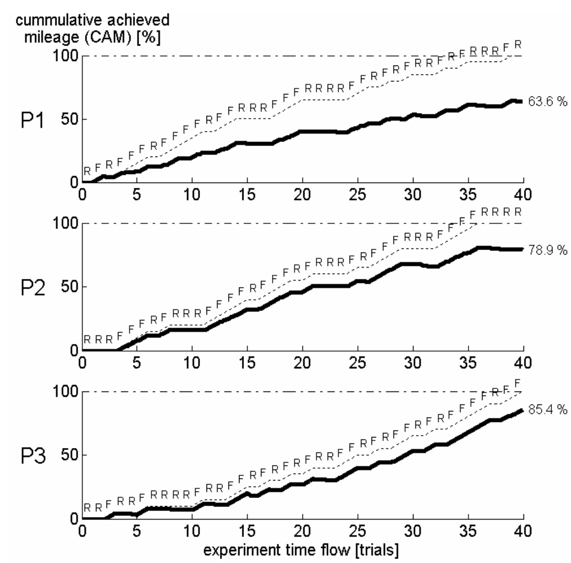

Figure 5: Task performance measures of all 3 participants (P1, P2 and P3) displayed in the theoretical possibility CAM (dashed line) and the real CAM (full line).

3.3. Presence and body representation

After completing the experiments in the Cave, the participants were asked to fill in the Slater-Usoh-Steed presence questionnaire [22] and then a non-structured interview was conducted. The results of the questionnaire and interview data have been evaluated separately [23]. After the standard BCI experiments and after the HMD experiments no presence questionnaires and interviews have been conducted. As a result of that no comparable analysis can be done over the three FB conditions and therefore this topic can not be discussed further in this paper, nevertheless the BCI may be considered as a very unusual extension of the body.

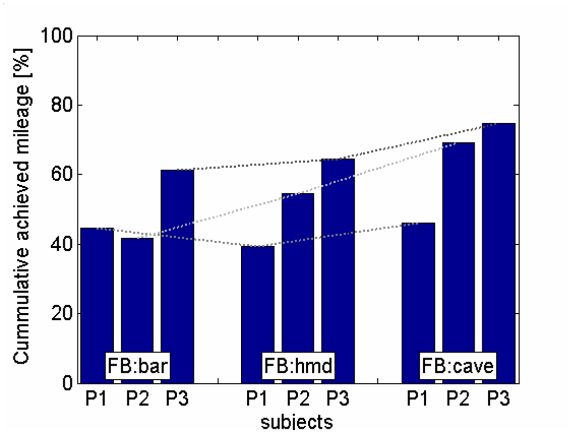

Figure 6: Mean CAM values of all participants and all 3 FB conditions. The trend of each participant over the FB conditions is plotted as grey dashed line.

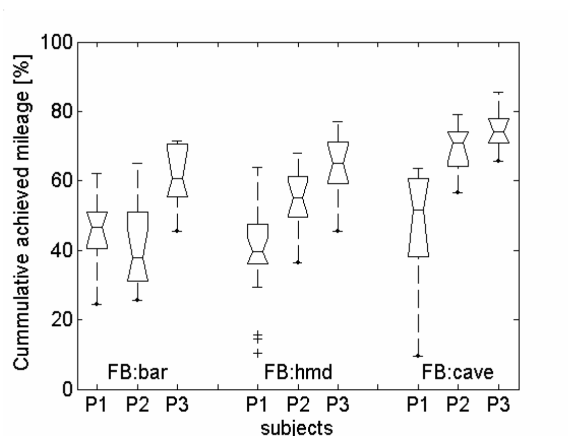

Figure 7: Distribution of the achieved CAM of all participants and all 3 FB conditions. Each plot has lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of the box to show the extend of the rest of the data.

4. Discussion and conclusion

These data indicate that EEG recording and single trial processing are possible in a HMD or a Cave-like system, and that feet motor imagery is an adequate neural strategy to control events within the VEs. Imagination of both feet movement is a mental task which comes very close to that of natural walking. The next important step in this research is to change the experimental paradigm to eliminate externally-paced cues. In this way the participant could decide to start walking at will. Such an asynchronous BCI system however, is more demanding and more complex for the participant [24].

The participants were able to achieve a grand average CAM of 49.2%. The result of a random session would be a CAM of 0%. Relative good performances are obtained with the virtual FB's (Cave better than HMD), except some outliers. One reason for some inferior classification results of individual runs especially in the Cave condition in Figure 7, e.g. CAM of 9.5 in participant P3) could be the loss of concentration in connection with a moving visual scene, because observation of moving objects can have an impact on neurons in the motor area [25]. Another possible explanation for the problems in the performance results of participant P1 (top row in Figure 5) could be that between trial 14 and 17 and between trial 20 and 25, the same class always should have been performed, that is the "standing class" (right hand movement) in this example, but the participant wasn't able to remain stationary for such a long period. A similar effect can be observed at the end of the run plotted in the middle row of Figure 5. Perhaps a faster alternation between the two classes would achieve better results, but the sequence of cues was randomized automatically through each run. The problem of this long period of "standing" is that during this time no feedback is given to the participant. If the correct movement (right hand motor imagery) is imagined, the participant remains stationary, but if the wrong movement (foot motor imagery) is imagined, then the participant walks backwards. Walking backwards is visual feedback, in contrast to remaining stationary, so the period of giving no information back to the participant is broken. It can also be observed that the way which was walked backwards isn't that steep and long as the path forward.

The task performances (see Figure 6 and 7) and the BCI classifications (see Figure 3) achieved the best values during the Cave-FB. The argument that only the task experience triggered this result can be disproved, because the conditions were recorded in another sequence and unfortunately the classification error increased in participant P1 over the time (see Figure 4), which would be contradictory to that argument. Whether a VE or an immersive VE as feedback has an impact on the performance or can shorten the training time needs further investigation. The number of participants is too small to allow statistical analysis, but the results are consistent. All subjects reported that the Cave was more comfortable than the HMD and both were very much preferred over the BCI training on a monitor.

In principle should it be possible to achieve the same performances in both VE conditions, the HMD and Cave. The limited field of view (FOV) of the HMD and the weight on the head was irritating and bothering. Also the optical resolution of the HMD was less than in the Cave. Therefore the subjects felt less present with the HMD as in the Cave. The Cave was compared to the HMD as a VE-FB much more natural and is hence preferable.

The main reason given for preferring the VR was that it provided motivation. The street was treated as a sort of race course and every subject wanted to get further as the others in the previous sessions. The motivation seems to greatly improve BCI performance, but too much excitement might have a negative impact, as it makes it harder to concentrate on the BCI control. Two subjects had sometimes nearly perfect runs till the last 2 or 3 trials of the run. At that time they already realized that they could achieved a new distance record, but this excitement reduced their concentration and therefore the last trials were performed badly, which reduced the task performance insomuch that no new record could be achieved. The aspect of motivation and the task/goal of the subject during the experiment have a great influence on the BCI performance and must be taken into consideration in all further BCI experiments.

VR provides an excellent training and testing ground for procedures that may apply later in reality. One important application may the use of VE for people with disabilities. If it can be shown that within VE people can learn to control their movements through space, than this justifies the much greater expense of building physical devices (e.g. neuro-prosthesis or a robotic arm) that are controlled by a BCI. Another application of the combined BCI and VR is the use of the VE with the goal to will enhance the classification accuracy and shorten the time needed for BCI trainings session. Feedback presentation by using VR is very powerful and may improve the biofeedback therapy as e.g. to reinforce the rehabilitation in stroke patients.

The research reported in this paper is a further step to the long-range vision for 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 [3, 24, 26]. The ultimate idea behind is to use direct implants into the brain (for completely paralyzed patients) for computer control, as discussed recently by Nicolelis [27] and analyzed directly the activity of single neurons. In this case the signal-to-noise ration and more than 2 mental states can be classified with high accuracy.

Maybe the vision of the science fiction authors to use the brain as the ultimate interface will become reality sometime in the future.

Acknowledgements

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