Thinking Penguin: Multi-modal Brain-Computer Interface Control of a VR Game

Robert Leeb, *Member, IEEE*, Marcel Lancelle, Vera Kaiser, Dieter W. Fellner, Gert Pfurtscheller

***Abstract*— We describe a multi-modal brain-computer interface (BCI) experiment, situated in a highly immersive CAVE. A subject sitting in the virtual environment controls the main character of a virtual reality game: a penguin that slides down a snowy mountain slope. While the subject can trigger a *jump* action via the BCI, additional steering with a game controller as a *secondary task* was tested. Our experiment profits from the game as an attractive task where the subject is motivated to get a higher score with a better BCI performance. A BCI based on the so-called brain-switch was applied, which allows discrete asynchronous actions. Fourteen subjects participated, of which 50 % achieved the required performance to test the penguin game. Comparing the BCI performance during the training and the game showed that a transfer of skills is possible, in spite of the changes in visual complexity and task demand. Finally and most importantly, our results showed that the use of a secondary motor task, in our case the joystick control, did not deteriorate the BCI performance during the game. Through these findings, we conclude that our chosen approach is a suitable multi-modal or hybrid BCI implementation, in which the user can even perform other tasks in parallel.**

***Index Terms*— Brain-Computer Interfaces (BCI), virtual reality (VR), game, multi-tasking, hybrid BCI, multi-modal, brain-switch**

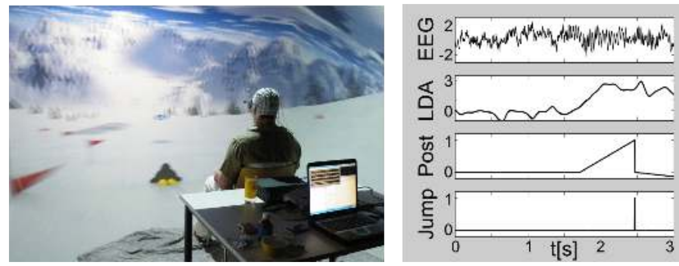

Fig. 1. The left side displays a subject in the virtual environment during the penguin racer experiment. The penguin should jump up to collect the fish. This is triggered by the user with the Brain-Computer Interface, whereby an exemplary output is shown on the right side.

I. Introduction

For a long time, Brain-Computer Interfaces (BCI) for Virtual Environments (VE) have been the subject of many science fiction stories. Often, a complete immersion and a direct mapping of thoughts to actions in Virtual Reality (VR) are described or dreamed of, but in reality, the possibilities are still quite limited. Nevertheless, the promising potential of this BCI-VR combination is visible at two levels. On one hand, BCI is seen by the VR community as a new input device that may completely change the way to interact with VEs [20]. On the other hand, VR technologies also appear as useful tools for BCI research. VEs can indeed provide a richer and more motivating feedback for BCI users than traditional feedbacks that are usually in the form of a simple 2D bar displayed on screen. Therefore, a VR feedback could enhance the learnability of the system, i.e. reduce the amount of time needed to learn the BCI skill, as well as increase the mental state classification performance [22], [39]. VEs can also be used as a safe, cost-effective and flexible training and testing ground for prototypes of BCI applications. For instance, it could be used to train a patient to control a wheelchair with a BCI [21] and to test various designs for the wheelchair control, all of this without any physical risk and at a greatly reduced cost. As such, VR can be used as an intermediary step before using BCI applications in real-life.

Most BCIs are based on the real-time analysis of non-invasively recorded electro-physiological brain signals, by means of the electroencephalogram (EEG). Control parameters are extracted from this activity, which can be used by disabled or healthy people to establish a new communication channel between the human brain and a computer. Generally, two different neurophysiological phenomena of the EEG can be used as input to a BCI: either (i) event-related potentials (ERPs) which are time-locked responses to an external event, or (ii) event-related oscillatory changes, which are internally induced modulations in the ongoing EEG. In particular, the mental imagination of movements is a very popular and widely used mental strategy [51]. It is described as the mental rehearsal of a motor act, without any overt motor output [4] and results in an amplitude suppression or enhancement of Rolandic mu rhythm (7–13 Hz) and the central beta rhythm (13–30 Hz) recorded over the sensorimotor cortex of the participant [32], [34]. It is broadly accepted that mental imagination of movement involves similar brain regions to those which are used for programming and preparing such movements [5], [13]. During

Correspondence to Robert Leeb (robert.leeb@epfl.ch).

R. Leeb, is with the Chair in Non-Invasive Brain-Machine Interface, Center for Neuroprosthetics, École Polytechnique Fédérale de Lausanne, Station 11, CH-1015 Lausanne, Switzerland.

M. Lancelle is with the Fraunhofer IDM@NTU, Nanyang Technological University, Singapore and with the Institute of Computer Graphics and Knowledge Visualization, Graz University of Technology, Inffeldgasse 16c, A-8010 Graz, Austria.

V. Kaiser is with the Laboratory of Brain-Computer Interfaces, Institute for Knowledge Discovery, Graz University of Technology, Inffeldgasse 13, A-8010 Graz, Austria.

D. W. Fellner is with the Institute of Computer Graphics and Knowledge Visualization, Graz University of Technology, Austria, with the Interactive Graphics Systems Group (GRIS), Technical University Darmstadt, Germany and with the Fraunhofer Institute for applied research in Visual Computing (IGD) in Darmstadt, Germany.

G. Pfurtscheller is Emeritus Professor at the Laboratory of Brain-Computer Interfaces, Institute for Knowledge Discovery, Graz University of Technology, Inffeldgasse 13, A-8010 Graz, Austria.

the operation of the BCI, the user's task is to intentionally "produce" certain brain states (i. e. EEG patterns) that can be detected by the system. Before being able to use a BCI, the subjects have to learn to voluntarily modulate the EEG oscillatory rhythms by performing the imagery tasks and the BCI system has to learn what the subject-specific patterns are. Therefore several training sessions are necessary before a BCI can be used for reliable control purposes. The duration of the training varies widely from subject to subject and can last from several hours to many months [30], [9]. Furthermore, the temporal dynamics and the accuracy of a BCI controlled channel cannot be compared with a normal manual control. First, brain patterns need time to evolve (in case of oscillatory activities some seconds); second, the signal-to-noise ratio of the EEG is not so high, therefore the BCI accumulates the evidence (integration, averaging…) before delivering decisions; third, brain patterns vary slightly each time the mental task is performed; and fourth, the number of tasks or imagination to be differentiated is limited and therefore the information-transfer rate or bandwidth is relatively low [51].

Important points in realizing a practical and usable motor-imagery BCI are: (i) to have stable EEG features for detection and control, (ii) to need only a short training time and (iii) to use only a small number of EEG derivations. All these points are fulfilled when the beta-rebound, a short-lasting event related synchronization (ERS), is used for classification [35]. For this purpose the EEG signals are recorded during imagination of brisk dorsi-flexions of the feet. Offline simulation of an asynchronous BCI showed that it is suitable for realizing an asynchronous brain-switch [45].

Furthermore, BCIs have recently been extended and combined with assistive technologies or other brain and body signals to develop more reliable and practical systems, which are called hybrid BCIs [27], [28]. Various types of hybrid BCIs exist, since such a system might use several input channels either sequentially by switching between them [15], or together by fusing various inputs [24], or multiple in parallel to increase the number of control channels. In [29] the basic requirements are described, which are: (i) it must provide volitional control, (ii) it must rely on brain signals, (iii) it must provide feedback, and (iv) it must work online.

BCI and recently hybrid BCI have been used to control game-like environments. In the beginning, simple games like the basket game [14] or Pacman [16], or later flight-simulators [26], 3-D games [17] or ego-shooters [36] were used, whereby in all examples the BCI was exclusively replacing the normal control modality. Lately, multi-modal interactions (MMI) and hybrid principles were applied for controlling games in healthy persons in VR [37], [41]. More information about the mutual benefits between MMI and BCI is given in [10].

Nevertheless, the influence of secondary tasks (of multi-tasking) on such BCIs or hybrid BCIs have not been thoroughly investigated up to now. Especially if we want to move BCI control out of laboratory conditions towards real-world applications, the BCI user will start performing other tasks in parallel to the BCI control. These secondary tasks require part of the participant's attention, which has to be shared, and of course can involve similar or correlated brain areas. Recently, Tavella et al. [48] demonstrated that healthy subjects can mentally control a non-invasive BCI-controlled neuroprosthesis for the restoration of grasping while performing a handwriting task. Tonin et al. [49] showed how users and Carlson et al. [2] how patients can mentally control a telepresence robot via the BCI to perform a navigation task in daily environments. All experiments give a short glimpse of the idea that users can successfully perform BCI control, which can be superimposed on a secondary task.

In this work we show a multi-modal approach of using an asynchronous BCI in parallel with a manual joystick control signal, while playing a game in VR (see Figure 1). In particular, we want to demonstrate that we can quickly set up such a BCI control, can transfer the BCI performance to the hybrid application, while showing that the secondary task does not influence our BCI performance.

II. Methods

In this section the choice of participants and the data acquisition of the various bio-signals are described. The initial BCI screening, feature extraction, classifier setup and the online test in the laboratory environment are explained, which were all performed on the first day (session 1). On another day (session 2) the VR game experiment (penguin racer) was performed, therefore, we describe the adaptation of the game, the game play itself and the four tested experimental conditions. The time between the two sessions for each subject was within 6–16 weeks.

A. Participants and Bio-signal Data Acquisition

Fourteen healthy subjects (12 male and 2 female, age 27 ± 2 years) participated in this experiment. The subjects were right handed, had normal or corrected to normal vision and were paid for attending the experiments. The study was approved by the local ethics committee and was in line with the declaration of Helsinki. In both experiments, each volunteer was comfortably seated in a chair in front of the screen, once about $1.5\,\mathrm{m}$ in front of a normal monitor for the training experiment and once in the center of a DAVE (Definitely Affordable Virtual Environment, [7]), a cubicle with $3.3\,\mathrm{m}$ wide walls, while wearing shutter-glasses (see Figure 1 for the VR experiment).

An electrode cap (Easycap, Germany) was fitted to the subject's head, and the EEG electrodes (Ag/AgCl electrodes) were placed according to the extended 10/20-system [12] (see Figure 2). One Laplacian channel was recorded over the foot representation area (Cz and the four orthogonal positions $2.5\,cm$ to Cz), by removing the weighted average of the surrounding four electrodes from Cz [11]. Such a setup was shown to be suitable for recording brain patterns during the imagination of brisk foot dorsi-flexion [45], [35]. The reference was placed at the left mastoid and ground at the right mastoid. The EEG recordings had a dynamic range of $\pm 100\,\mu\mathrm{V}$. The signals were analog band pass filtered ($0.5\,\mathrm{Hz}$ to $100\,\mathrm{Hz}$) and notch filtered at $50\,\mathrm{Hz}$. The impedances of all channels were below $5\,\mathrm{k}\Omega$.

Furthermore, one electromyogram (EMG) channel was recorded bipolarly from the leg, whereby the electrodes were placed over the *musculus tibialis anterior* of the right leg (see Figure 2). The EMG was amplified, band-pass filtered between 1 and 1000 Hz, base-line-corrected, full-wave rectified, and integrated with a 100 ms time constant by a custom-made amplifier (TU-Graz, Austria) to extract the envelope before the digitization. All bio-signals were sampled in parallel with a sampling frequency of $f_s = 250\,\mathrm{Hz}$.

The recording system consisted of one 16-channel bio-signal amplifier (g.tec, Guger Technologies OEG, Graz, Austria) for the EEG, one data acquisition card (DAQ-6024E, E-Series, National Instruments Corporation, Austin, USA) to digitize all the signals and a standard personal computer running the Windows XP operating system (Microsoft Corporation, Redmond, USA). The recording was handled by rtsBCI [40], based on MATLAB 7.0.4 (MathWorks, Inc., Natick, USA) in combination with Simulink 6.2, Real-Time Workshop 6.2 and the open source package BIOSIG [43]. The EEG and bio-signal recordings were saved into the gdf-format (General Data Format for biomedical signals, [42]).

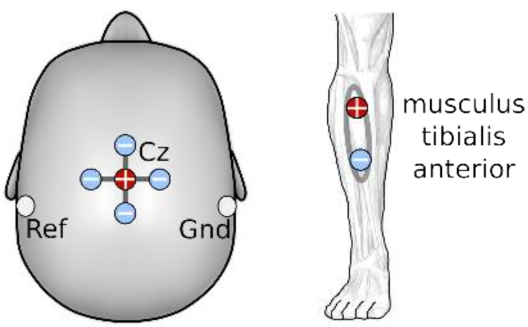

Fig. 2. Location of the EEG electrodes, viewing the head from above. The Laplacian channel over *Cz* was used for control. Dark red circles mark the positive and light blue circles mark the negative electrodes for the Laplacian derivation. The distance between the electrodes was 2.5 cm. The reference electrode was on the left and the ground on the right mastoid. On the right side, the location of the EMG electrodes on the right leg placed over the *musculus tibialis anterior* is shown.

B. Initial Screening without Feedback

Before the actual VR experiment, an initial screening was performed on a separate day (session 1) with the following paradigm: A cue on the screen lasting for 1.25 s instructed the subjects to imagine a brisk foot movement. Subjects were expected to imagine a *brisk dorsiflexion of both feet*, which should last less than 1 s. A green cross in the middle of the screen lasting from 2 s before until 1.25 s after the cue, informed the subjects about the start and end of each trial. Afterwards, a blank screen was shown for a random duration between 3.5 s and 9.5 s (see Figure 3 for more timing details). They were asked to keep their arms, hands and feet relaxed and to avoid eye movements during the experiment. Three runs were performed containing 30 trials each, whereby the duration of one run was approximately 5.5 min.

Besides the runs with motor imagery (MI), also one run with motor execution (ME) of the same brisk dorsiflexion of both feet was recorded, to compare the brain patterns. The only difference in the timing was that the random time between the trials was reduced to a duration between 1.5 s and 3.5 s.

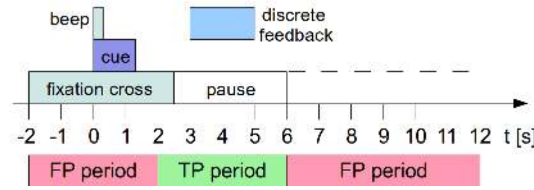

Fig. 3. Timing of a BCI trial with motor imagery (MI) for screening and self-paced feedback recordings. The cue was displayed at second 0 together with a beep. The subjects were instructed to perform the brisk foot movement as fast as possible. Afterwards there was a pause with a fixed duration of 3.5 s (solid box) plus a variable duration of up to 6 s (dashed box). In case of online trials, a discrete feedback event was displayed for 2 seconds on the screen, whenever the classifier detected the pattern (e.g. here at second 3). The time period in which such a detection was counted as a correct one (TP) was 4 seconds long, marked in green as TP period, otherwise it was counted as a wrong detection (FP), marked in red as FP period. For runs with motor execution (ME), the pause time was reduced to a duration between 1.5 s and 3.5 s.

C. ERD/S Maps and Feature Extraction

Time-frequency maps [8] were calculated of the Laplacian channel for convenient data inspection. The map displays significant ($p < 0.05$, t-percentile bootstrap algorithm) band power changes within a frequency range of 6–40 Hz with a frequency resolution of 1 Hz and overlapping frequency bands of 2 Hz. 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 [31]. An example for such an ERD/S map is illustrated in Figure 6.a. We expect to find a short peri-imagery ERD during the imagination of a brisk movement [31] and a strong post-imagery ERS (beta-rebound, [33]) afterwards.

For the selection of the most informative features the Distinction Sensitive Learning Vector Quantization (DSLVQ, [38]), an extended version of Kohonen's Learning Vector Quantization algorithm was used. Very briefly, in this approach the DSLVQ uses a number of codebook vectors (labeled reference vectors) with a weighted distance function to approximate the optimal Bayesian decision borders between different classes. During the learning process, the influences of features that contribute to misclassification are discarded and most informative features are boosted. Finally, each sample is identified to the label of its closest codebook vector (for details see [38]). The major advantage of DSLVQ is that it neither requires expertise, nor any a priori knowledge or assumption about the distribution of the data. Furthermore, not only relevant features, but also feature combinations are identified.

Logarithmic band power features (logBP) of 17 non-overlapping frequency components between 6 and 40 Hz with a bandwidth of 2 Hz were computed by digitally bandpass filtering the EEG signal, squaring and averaging the samples in the analyzed 0.25 s time window. The DSLVQ was trained with these logBP features of the MI class over the whole trial time (from $-2\,\mathrm{s}$ to $6\,\mathrm{s}$, in steps of $0.5\,\mathrm{s}$) compared to the baseline period (-2 to $0\,\mathrm{s}$). In order to obtain reliable values for the feature relevance [38], the DSLVQ method was repeated 100 times. In each repetition 50 % of the logBP features were randomly selected for training and the remaining 50 % were used for testing. The DSLVQ used a type C training with 10 000 iterations, while the learning rate α decreased from 0.05 to 0. For the DSLVQ relevance values a learning rate of $\alpha'(t) = \alpha(t)/10$) was taken. Finally, the most relevant features were selected by evaluating the feature relevance from the DSLVQ analysis, where a high value represents an important feature.

D. Classifier Setup and Post Processing

For each subject one selected frequency band for the post-imagery ERS ($\mathrm{FB_{ERS}}$) and one band for the peri-imagery ERD ($\mathrm{FB_{ERD}}$) were used to train a linear discriminant analysis (LDA), whereby adjacent features were combined to one large feature (e.g. in case of subject S8 bands 26–28 Hz, 28–30 Hz, 30–32 Hz and 32–34 Hz were combined to 26–34 Hz). The ERD feature for the LDA classifier was delayed by a subject-specific time $t_{\mathrm{del\_ERD}}$ extracted from the DSLVQ map, to be aligned with the ERS feature. Fisher's LDA [1] uses a linear hyper-plane to discriminate between the different classes (in our case, samples from the baseline and the ERS period, which time interval was taken from the DSLVQ and ERD maps).

The post processing generated a control signal only when the LDA output of the MI exceeded a selected threshold (Th) for a selected dwell time (t_{dwell}, between $0.5\,\mathrm{s}$ and $1.5\,\mathrm{s}$) [50].

The threshold was defined for each subject as the mean plus one standard deviation of the classifier output during the time of the fixation cross and the dwell time was selected as half of the time over this threshold during the imagery period. The detected events were transferred into control commands for the feedback. After every event a refractory period of $4\,\mathrm{s}$ was applied during which event detection was disabled.

E. Cue-based Imagery with Self-paced Feedback

For the online feedback experiments we used the same timing as in the screening runs. The only difference was that we continuously analyzed the EEG (asynchronous BCI). If the classifier detected the movement pattern, a discrete feedback event was displayed on the screen for 2 seconds, see Figure 3. We want to point out that the classification and the feedback could happen at any time, meaning inside a trial period or outside. Generally the subjects were instructed by the cue to perform the brisk foot motor imagery. In case the movement was detected inside the 4 seconds long period, it counted as a true positive detection (TP). If the detection was outside this time, either too late or within the pause time, it counted as false positive (FP). Trials in which no detection occurred during the feedback time were counted as false negative (FN). Three runs, each with 30 cues, were recorded on the same day as the screening (session 1).

The true positive rate (TPR), false positive rate (FPR) and the positive predictive value (PPV) were calculated according to [6] as

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \cdot 100\ [\%]$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TN}+\mathrm{FP}} \cdot 100\ [\%]$$

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \cdot 100\ [\%].$$

The TPR indicates the ratio between correctly detected commands by the BCI and all commands intended by the subject, specified via the cues. The FPR indicates the ratio between the wrongly detected commands by the BCI and the maximum possible commands delivered outside the intended period which is computed by dividing the maximum duration by the dwell time and refractory period. The PPV indicates the ratio between correctly detected commands and all commands detected. All values are between $0\,\%$ and $100\,\%$, where a TPR of $100\,\%$ implies that all intentions of the participant were detected successfully, while a PPV of $100\,\%$ means that all detected commands were intentionally delivered by the participant. In contrast, an FPR of $0\,\%$ indicates that the BCI did not wrongly detect any intention.

F. Virtual Reality Setup

The DAVE [18] is a four sided CAVE [3], a projection room with front, left and right rear-projection walls as well as a floor projection from above. Compared to a normal monitor or projection, the user has a much wider field of view. The 3D projectors show the images for the left and right eyes in quick succession and the user wears shutter glasses for stereoscopic separation. In addition, the head position and orientation are measured with an optical tracking system, allowing the estimation of the user's eye positions and to show a perspectively correct image. This enables a user e.g. to see objects from different sides by walking around them within the DAVE. This parallax effect often remarkably increases immersion. However, in our experiment the subjects could hardly profit from the head tracking, as they sat on a chair and were requested not to move their head too much in order to avoid motion artifacts in the EEG signals. We used shutter glasses for stereoscopic separation and optical tracking for perspectively correct viewing.

Most of the DAVE hardware consists of off-the-shelf components, allowing the costs to be kept low and the system to be kept up to date by replacing the graphics hardware and the PCs every few years. For maximum performance, each left and right image of each projector is computed by a dedicated PC. These eight PCs are controlled by an additional server that handles user input and synchronizes the application state to the rendering clients [18], [19].

G. Adaptation of the Game to the Virtual Environment

Creating rich virtual environments with models and textures requires a lot of skill and time, especially since the participants are biased with their expectations towards the up-to-date high-end graphics of computer games. To save work, we chose to modify the existing open source game PPRacer [47], a successor of Tux Racer, where a penguin slides down a snowy track while collecting fish (see Figures 1 and 4.a). It has already been modified by us to run in the DAVE and was presented as an example for intuitive navigation in [46]. We use the Davelib [19] for necessary changes for the DAVE, mainly for network synchronization and correct view setup including head tracking. The same program is started on a master and every rendering client. The game is controlled only on the master that sends the few necessary state variables to the clients, like the new position of the penguin.

For a correct stereoscopic rendering, the skybox of the game had to be modified. It was originally very small and painted as background, resulting in an irritating wrong depth perception in a stereoscopic setup. The 2D overlay headup displays, initially visible on each screen, were removed. The game menu structure is skipped to immediately start the game.

The interface to the BCI computer is realized via UDP messages, where the BCI computer sends commands to the DAVE master PC. This includes commands to trigger a jump, to control the speed and to reset the game. To later analyze the results together with the BCI data, we also added a log file with time stamps to regularly record the penguin position, BCI commands and information about whether a fish was collected or not.

H. The Penguin Racer Experiment

Instead of looking from the point of view of the penguin, the subject observes the scene from a point higher above ground, following the penguin. This gives a better overview and allows for an easier control, as the orientation of the character is directly visible (see Figure 4.a).

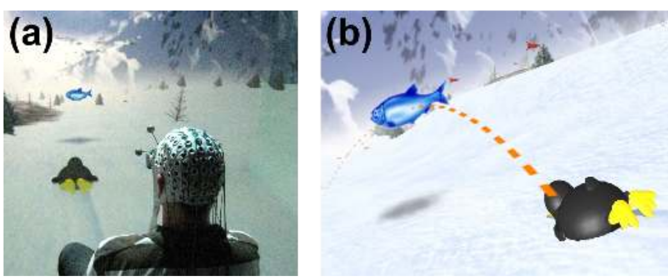

Fig. 4. (a) The subject observes the scene from a point following the penguin. (b) Intended flight path of penguin. It is necessary to trigger the jump well in advance, otherwise the penguin will not catch the fish.

For the experiment, the fish were moved up, to a couple of meters above the ground, so they could only be collected when the penguin jumped. By delivering a command with the BCI, the penguin jumped and flew in a vertically curved path continuing into the direction of the last movement on the ground (see Figure 4.b). The fish could only be collected when the penguin hit it. The flight curve and speed of the penguin were tuned so that it was possible to fulfill the task. Note that false positives lead to accidental jumps that are penalized by the game in a natural way: a new jump can only be started after landing, and turning is not possible during the jump. Each run lasted approximately 3 min and consisted of 12 fish with an inter-fish distance between 11.1 to 18.6 seconds (mean $\pm$ standard deviation (SD) = 13.7 $\pm$ 2.4 s). The number of collected fish was counted as the true positives (TP), the number of missed fish as the false negatives (FN) and the wrongly performed jumps as the false positives (FP). With wrongly performed jumps we mean the jumps which either collected no fish (e.g. jumped too early, too late or to one side) or whenever a jump was triggered without even a fish around. Furthermore, we define the task performance as the ratio of the number of successfully collected fish over the total amount of available fish.

We performed the experiment in two navigation modalities (Table I): first the participant played the game while pressing a push-button to trigger the jumps. In the second modality they used the brisk foot motor imagery detected by the BCI to trigger the jump. We applied the same dwell time and refractory period for the push-button condition as in the BCI one, to be able to compare the results.

Furthermore, two levels of difficulty were created and the fish were placed appropriately (Table I). In the first level, all fish are placed in a straight line and can be collected without steering the penguin. In the second level, steering with the joystick is necessary in parallel to the jump to be able to collect all the fish (see Figure 5). We used the original steering of the game. Note that this steering is not direct but instead, the maximum direction angle change rate is rather limited. This constraint was implemented in the original game to make it more challenging.

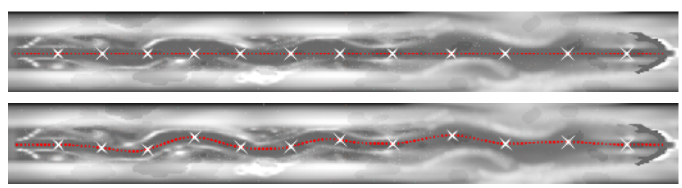

Fig. 5. Maps of each level showing the placement of the 12 fish with an "x". The penguin slides from left to right. The top level shows the fish placed in a straight line, where no steering is required (conditions MS and BS). At the bottom level the subject needs to use an additional joystick in order to catch the fish (conditions MC and BC). A possible good path is indicated by the red dots.

I. Experimental Conditions

The final experiment (session 2) consisted of the following four conditions (see also Table I):

1) Condition *MS*: A jump of the penguin is triggered by pressing the manual push-button, but no parallel use of the joystick control is necessary (because all fish are aligned in a straight line).
2) Condition *BS*: A jump of the penguin is triggered with the BCI, but no parallel use of the joystick control is necessary (because all fish are aligned in a straight line).
3) Condition *MC*: A jump of the penguin is triggered by pressing the manual push-button, and an additional joystick control is necessary to reach all the fish (because all fish are aligned in a curved path).

TABLE I

FOUR EXPERIMENTAL CONDITIONS WERE TESTED: CONSISTING OF TWO NAVIGATION MODALITIES EITHER WITH OR WITHOUT JOYSTICK CONTROL BY HAVING THE FISH ALIGNED STRAIGHT OR CURVED, AND TWO CONTROL MODALITIES FOR TRIGGERING THE JUMPS EITHER VIA MANUAL PUSH BUTTON OR BCI CONTROL.

		navigation modality	
		straight (no secondary task)	curved (parallel joystick use)
jump triggered	manual button	**m**anual **s**traight *MS*	**m**anual **c**urved *MC*
	BCI	**BCI s**traight *BS*	**BCI c**urved *BC*

4) Condition *BC*: A jump of the penguin is triggered with the BCI, and an additional joystick control is necessary to reach all the fish (because all fish are aligned in a curved path).

In the conditions MC and BC the participants used their right hand to control the joystick. In the conditions MS and MC the push-button was pressed with their left hand. In the conditions BS and BC the brisk foot motor imagery was used. We want to emphasize that it was possible to steer the penguin and jump at the same time, meaning that BCI and manual control were processed in parallel. However, in the conditions MC and BC, steering had no effect during the flight (penguin in the air), so that the penguin continued to travel in the direction of the last movement on ground.

We recorded three runs with manual control (MS and MC) and six runs with the BCI control (BS and BC). We first performed the experiment with no parallel control (MS and BS) and after a ten minute break with the joystick in parallel (MC and BC). Inside each block we interleaved the BCI and manual runs in the following order: 1×manual run, 3×BCI, 1×manual, 3×BCI and the final 1×manual run.

On the day of the VR experiment (session 2), we started to record 1×ME and 1×MI run to compare with the initial data and to check if the threshold should be adapted (see section II-D and Table II). Afterwards, we familiarized the subject with the penguin racer and gave them the possibility to explore the VR environment and to try the different navigation conditions (push-button, joystick, BCI), before the four experimental conditions were recorded. The whole experiment lasted approximately two hours per subject.

J. Post-experimental Questionnaire

After completing the VR experiments in the DAVE, the participants were asked to fill in a modified SUS (Slater-Usoh-Steed) presence questionnaire [44] containing 30 items, and were encouraged to give additional comments. The purpose of these 30 items was to get a subjective rating of several topics concerning presence (e. g.: overall sense of presence, sense of being there in the landscape; sometimes the landscape was reality for me. . .), environmental conditions (e. g.: I was aware of background sounds from the laboratory. . .), familiarity with PC and games (e. g.: usage of a PC in daily life. . .), preference for the conditions (BCI and push-button; straight or curved game; mental demand), questions concerning subject's success and suggestions for improvements. For 23 items they had to rate their subjective feelings on a 6-point scale. Seven items were designed as open questions.

III. RESULTS

In this section, first the subject-specific feature selection and the results of the cue-based training are presented. Next, the outcomes of the penguin racer experiment are described, before the statistical analysis is performed. Then, some offline simulations and optimizations are carried out to compare the results. At the end, the EMG data and the questionnaires are analyzed.

A. Feature extraction and classifier setup

The subject-specific frequency bands for the post-imagery ERS and peri-imagery ERD features are given for all subjects in Table II, together with the delay for the ERD band and the classifier threshold and dwell time. Not all subjects showed the ideal brain patterns, so we were not always able to find corresponding frequency bands. In subjects S3 and S6 we did not find any beta-rebound (ERS), just an imagery ERD, which was valid in case for the ME data. Subject S11 showed only an ERS in the execution run, but nothing in the MI ones. Finally, the recordings from subject S12 had a very bad signal quality and we could not find any discriminative brain patterns. These subjects were not selected to perform any online runs (session 2).

Figure 6.a shows the ERD/S map of one representative subject. Subject S8 is chosen because the performance and delay for the ERD feature are close to the mean of all subjects. The bands selected by the DSLVQ algorithm are marked (14–24 Hz for the ERS and 26–34 Hz for the ERD, see Table II). On the top right the evolutions of the ERD and ERS features over time are displayed (Figure 6.b). As mentioned in section II-D, the ERD band values were subject-specifically delayed (for this subject by 1.7 s; see all values in Table II) to be aligned with the ERS feature. The resulting output of the LDA classifier with dwell time and threshold is given in Figure 6.c.

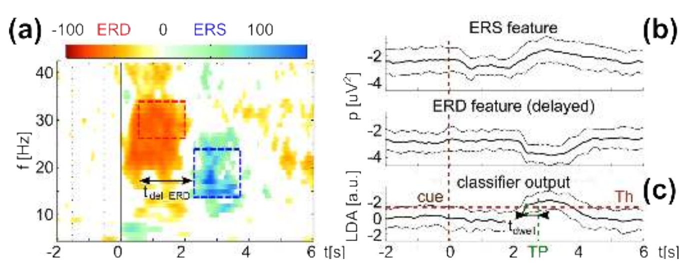

Fig. 6. (a) ERD/S map for subject S8. The bands selected by the DSLVQ algorithm are 14-24 Hz for the ERS and 26-34 Hz for the ERD. The cue is at second 0. (b) The evolution of the two selected features over time, the ERD band values are delayed by $t_{del\_ERD} = 1.7$ s to be aligned with the ERS ones. (c) The output of the remaining LDA classifier with dwell time (t_{dwell}) and threshold (Th) results in a detection (TP) at second 2.7.

TABLE II

SELECTED FREQUENCY (FB) BANDS FOR ERS AND ERD BY THE DSLVQ. THE ERD FEATURE WAS DELAYED BY T_{DEL_ERD} FOR THE LDA CLASSIFIER. DWELL TIME (T_{DWELL}) AND DECISION THRESHOLD (TH) FOR ASYNCHRONOUS DETECTION. A "—" SIGN MEANS THAT NO FEATURE OR THRESHOLD COULD BE IDENTIFIED. IF THE DECISION THRESHOLD WAS ADAPTED AT THE BEGINNING OF SESSION 2 (PENGUIN GAME) THE NEW VALUE IS GIVEN IN THE LAST COLUMN (TH_P). SUBJECT S12 HAD A VERY BAD SIGNAL QUALITY.

ID	FB_{ERS} [Hz]	FB_{ERD} [Hz]	t_{del_ERD} [s]	t_{dwell} [s]	Th	Th_P
S1	20-26	08-10	1.5	1.0	0.5	0.1
S2	25-32	28-35	2.3	0.8	0.4	
S3	—	20-24	1.0	1.0	0.7	
S4	20-26	24-28	2.0	0.8	0.7	1.0
S5	24-32	28-30	1.7	0.5	0.7	0.3
S6	—	18-26	2.2	—	—	
S7	32-34	16-20	1.8	0.8	0.4	
S8	14-24	26-34	1.7	1.0	1.5	
S9	22-26	26-30	2.0	0.8	0.5	0.1
S10	27-30	17-19	1.0	0.7	0.2	
S11	20-30	—	—	—	—	
S12	—	—	—	—	—	
S13	28-32	12-14	1.3	1.3	-0.2	
S14	34-38	18-26	2.2	1.0	0.5	

TABLE III

TPR, FPR AND PPV OF THE CUE-BASED IMAGERY RUNS WITH SELF-PACED FEEDBACK (SESSION 1).

ID	TPR [%]	FPR [%]	PPV [%]
S1	50.0	4.1	87.5
S2	71.3	4.1	90.5
S3	—	—	—
S4	78.8	19.3	70.8
S5	52.5	11.0	73.7
S6	—	—	—
S7	51.3	16.8	63.1
S8	43.8	7.7	77.8
S9	42.5	24.8	50.0
S10	30.0	20.3	47.1
S11	—	—	—
S12	—	—	—
S13	30.0	6.9	75.0
S14	23.8	25.6	35.8

B. *Cue-based Imagery with Self-paced Feedback*

The TPR, FPR and PPV values of the online run of session 1 are given in Table III. Five subjects achieved TPR values above $50\,\%$ with FPR below $20\,\%$, two even with FPR below $4\,\%$ or TPR above $70\,\%$. Two subjects had a PPV of close or equal to $90\,\%$, six had PPV values above $70\,\%$ and two subjects were better than $50\,\%$. The mean values were $47.4 \pm 17.6\,\%$, $14.0 \pm 8.3\,\%$ and $67.1 \pm 17.9\,\%$ for TPR, FPR and PPV, respectively. All subjects with a TPR above $40\,\%$ and PPV above $50\,\%$ (see Table III) were allowed to participate in the follow-up VR experiment. Unfortunately, subject S8 did not have time to participate any longer, therefore, only subjects S1, S2, S4, S5, S7 and S9 continued with session 2.

C. *Task Performance of the Penguin Racer Experiment*

The task performance in the penguin game in session 2 can be calculated as the ratio of successfully collected fish to the possible maximum, which is given in Figure 7. The performance in the manual push-button conditions (mean of $97.22\,\%$ (MS) and $93.52\,\%$ (MC)) are much better than in the BCI conditions (mean of $44.68\,\%$ (BS) and $47.69\,\%$ (BC)), statistically significant ($p < 0.005$, Kruskal-Wallis test) within each navigation condition. The result that manual control is better than BCI control is obvious and was expected from the beginning.

More interesting are the results within the same navigation condition (push-button or BCI), showing that the usage of the joystick did not interfere with the jump control. Results of the Kruskal-Wallis tests were not significant ($p > 0.5$ for both). Nevertheless, it is worth remarking that in the BCI conditions, a better performance could be achieved with (BC) compared to without joystick (BS). Although, each subject had a different performance level (varying between 33.3 % and 62.5 %, mean 44.7 %), each subject performed better or equal in condition BC (improvement between 0 % and 8.3 %, mean 3.0 %). These results are contradictory to the normally expected behavior, which would be $100\,\%$ performance for push-button alone (MS), close to $100\,\%$ in case of push-button with joystick in parallel (MC), because a slight distraction is assumed triggered by the more complex task. Moreover, we would have expected a strongly reduced performance in case of the BCI condition (BS), depending on the individual BCI performance and an even more decreased performance in case of BCI and joystick (BC), since the motor imagery to trigger the jump and the motor execution to control the joystick are conflicting with each other. However, this was not the case.

Taking a closer look at the task performance during BCI control, a slight improvement of the performance over the runs is visible, which is assumed to be a learning effect (see Figure 8). In both conditions the subjects adapted to the game requirements and (i) learned the timing when to deliver a

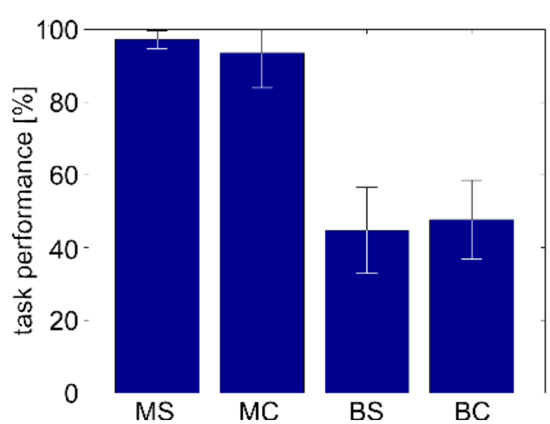

Fig. 7. Task performance of session 2 in percent: ratio of collected fish over the possible maximum. The bars correspond to the mean values (± standard deviation) of the four conditions (push-button (MS) / push-button and joystick (MC) / BCI (BS) / BCI and joystick (BC)). From left to right the conditions become more and more challenging.

TABLE IV
TPR, FPR AND PPV OF THE PENGUIN EXPERIMENT FOR THE FOUR CONDITIONS SEPARATELY AND MERGED FOR MANUAL AND BCI CONTROL (SESSION 2).

condition	TPR [%]	FPR [%]	PPV [%]
MS	97.2	1.0	97.2
MC	93.5	2.4	93.3
BS	44.7	18.7	50.9
BC	47.7	19.1	50.9
Manual	95.4	1.8	95.3
BCI	46.2	18.9	50.9

correct BCI jump command and (ii) to align the penguin with joystick correctly in front of the fish before triggering the jump so that the flight curve reached the fish. But no difference in the dynamics between the two conditions could be found, although all runs of condition BC were performed after BS. Between the runs of conditions MS and MC no difference and therefore learning could be found, because the participants already performed perfectly, after the familiarization before the experiment.

The mean values for TPR, FPR and PPV for each of the four conditions are given in Table IV. Interestingly, the TPR and FPR values from the merged BCI condition and from BS and BC individually are in a similar range and only slightly worse than (no statistical significant difference, $p > 0.05$, Kruskal-Wallis test) during the cue-based online session with self-paced feedback condition (session 1; compare to Table III; remember the mean TPR for the subset of 6 participants was 57.7 % and FPR was 13.4 %, and for all subjects TPR was 47.4 % and FPR was 14.0 %).

D. Influence of Joystick Control on the Given Task

In this work we are particularly interested in how the secondary task of controlling the position of the penguin via the joystick influences the main control condition. Hence, we subtracted the two behaviors from each other (with $-$ without joystick). The absolute difference for task performance, correct, wrong and missed jumps is given in Figure 9. The surprisingly positive task performance value in the BCI condition imply that the participants performed more correct jumps and missed fewer fish while performing the secondary task! This was not the case for the manual push-button condition, were two subjects improved (between +2.7 % and +5.5 %) but four subjects performed worse (between -2.7 %, -5.5 % and -19.4 %) with the secondary task. Especially subject S2 had a drop of nearly 20 %, more or less constantly spread over all runs.

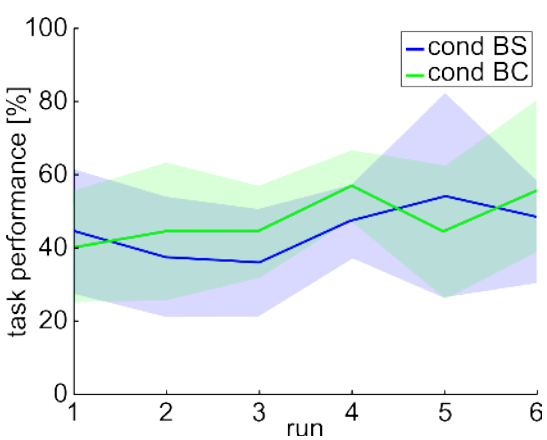

Fig. 8. Task performance (mean ± standard deviation) of condition BS in blue and BC in green separately for each of the 6 runs. A slight learning curve is visible in both conditions.

In both conditions (push-button and BCI) generally more incorrect jumps were performed while using the joystick control compared to without the joystick. But this result was expected since the subjects had to share the task between steering the penguin and triggering the jump at the correct time (either by BCI or push-button). Furthermore, we can remark, that a few jumps were triggered at the correct time (not too early or too late), but the penguin jumped physically beside the fish. One popular reason was that the penguin was not aligned perfectly (moving straight towards the fish) before the jump was triggered, because during the jump (penguin in the air) no correction of the jump direction was possible. Moreover, some subjects aligned the penguin correctly but sometimes missed the exact time to trigger the jump, so that the penguin was already in the air, but still too low to collect the fish, or already too low while coming down.

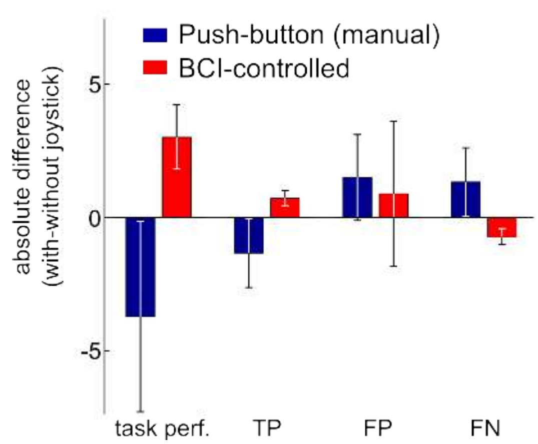

Fig. 9. The influence of the secondary task is plotted as the difference of absolute numbers between conditions without and with joystick control (mean ± standard deviation). The dark blue bars are from the manual push-button conditions and the light red ones from the BCI control conditions. Each pair of bars corresponds to the averaged run differences of task performance, collected fish (TP), the wrongly performed jumps (FP) and the missed fish (FN), respectively.

The number of wrongly performed jumps (either too early or too late to collect a fish, or in the periods in-between) in relation to the maximum amount of fish is also different between the control modalities. The number of wrong jumps in case of the push-button conditions were very small (2.8 % without (MS) and 6.9 % with joystick (MC)) compared to 48.4 % with BCI (BS) and 52.1 % with BCI and joystick (BC), The number of wrongly performed jumps increased slightly in both conditions with joystick, but Kruskal-Wallis tests per modality showed no statistical influence of the secondary task.

E. Offline simulations and decision parameter optimizations

Comparing the performances of session 1 (cue-based imagery with self-paced feedback) and session 2 (penguin racer experiment) is very complicated since different timings and strategies (cue-based, self-paced) were applied. In the case of the former, the timing is dominated by the cue instructing the subjects to perform the MI, whereby in the latter the subjects have to decide by their own when to start the MI to trigger the jump. Nevertheless, both conditions apply an asynchronous BCI, meaning that every performed MI was asynchronously detected. Furthermore, the time between the cues is different between the sessions; in session 1 11.21 ± 1.8 s (maximum of 14 s) were between the cues and in session 2 13.7 ± 2.4 s (maximum of 18.6 s) between the fish (which are the corresponding cues). Therefore, many more FPs can occur in session 2.

One way to compare the performances is to simulate the timing of one experiment and apply it to the data of the other one. We therefore extracted the subject induced timing variations of the two BCI conditions of session 2 (penguin experiment) and applied it to the timing of session 1, while using the original data (EEG, classifier and thresholds) of session 1. The resulting TPR, FPR and PPV values are 57.5 %, 14.7 % and 70.9 %, respectively, which are very close to 57.7 %, 13.3 % and 72.6 % achieved in session 1 (from Table III). Furthermore, the reverse condition was tested, by taking the timing of session 1 and applying it to session 2, while using the original data of session 2. The resulting TPR, FPR and PPV values are 43.1 %, 19.9 % and 45.9 %, respectively, which are slightly worse than 46.2 %, 18.9 % and 50.9 % achieved in the BCI control condition of the penguin game (from Table IV). The Kruskal-Wallis tests showed no statistical difference between the different conditions and simulations, meaning that the visual complexity and the more demanding task had negligible impact on the user's BCI performance.

Furthermore, it is very difficult to make a fair comparison between our online results with published offline studies. The challenge of every online experiment is that the decision parameters are never optimal compared to offline experiments, since they were optimized on data from earlier sessions. In particular, if the recordings are performed on different days, these parameters may not be optimal any longer. Therefore, an offline simulation of the BCI controlled penguin game is performed to find the optimal dwell time and decision threshold, but keeping the classifier (features, ERD feature delay, LDA weights) constant. If the same FPR ratio as in session 1 should be achieved, the mean TPR rate increases from 44.7 % to 60.4 % in condition BS and from 47.7 % to 64.8 % in condition BC, which is an improvement up to 44 % in BS and up to 132 % in BC for single subjects.

F. EMG Analysis

The EMG has been used in an offline simulation to identify which jumps could have been triggered by muscular activity. A subject specific threshold was defined as the mean plus one standard deviation of the whole EMG during the ME run (which consisted of 17 % samples with activity and 83 % without). For each subject this threshold achieved 100 % detection of the correct periods with 0 % of wrong detections in the ME run, and 0 % detections over the complete MI run.

Generally, in all conditions, no single jump could have been influenced or triggered by EMG activity during the foot imagery. Only 1 jump in condition BC in one subject (S7) was aligned with the BCI, which is less than 1.3 % of the jumps. But the same EMG activity would have triggered additional jumps in each subject and nearly each condition (which is not observable in online recordings)! In total, over all subjects, 12 additional jumps would be created in condition BC, 6 in BS, 13 in MC and 6 in MS, with a maximum of 7 additional jumps per subject and condition. More EMG activity was visible during the joystick navigation modality, which could come from the fact that steering the penguin was accompanied by moving the participant's body since the subject felt immersed in the virtual scene and therefore create more foot EMG activity.

Therefore, since no EEG-triggered jump correlated with the EMG activity, but additional jumps would be created by the EMG, we can exclude the possibility that participants used motor execution instead of the brisk foot motor imagery to trigger the jump of the penguin.

G. Questionnaire and Verbal Comments

The subjects were very positive about the game character and pleasing 3D scene, especially with the experience of training sessions and other experiments in mind. They rated the game on the 6-point scale (1= not at all to 6= very much) as more fun, enjoyable and engaging compared to the normal BCI feedback in session 1 ($x = 5.33$). Four subjects preferred the BCI control condition and only 1 subject the manual button, although the BCI condition was more demanding for them ($x = 4.67$). All enjoyed the curved conditions more than the straight ones ($x = 5.50$), and did not find them more stressful ($x = 3.83$).

When we asked about the sensation of "presence" via the SUS questionnaire two participants marked their sense of being in the virtual landscape with a five and four people with a four. Six persons even stated that they forgot almost all the time about the laboratory when they experienced the landscape and felt more like they were in the landscape than in the laboratory ($x = 4.33$). Questions concerning the environmental conditions showed that they were rather not aware of background sounds from the laboratory ($x = 2.33$) but a bit more aware of the experimenter ($x = 2.67$). On average they were not irritated by the goggles ($x = 2.17$). We asked to which extent the fact that they were sitting instead of standing while they were sliding through the landscape was irritating for the participants. Four of them rated this with "not at all" (1), one rated it with a (2) and only one person marked the (6) on the scale.

IV. Discussion

This work supports our claims that: (i) a good asynchronous BCI control of a VR game is possible with very short

BCI training. (ii) A VE is a very good training and testing environment for BCI applications. (iii) The use of a discrete event is an appropriate control signal for such a game-like environment. (iv) No performance difference between online training sessions and sessions with the penguin could be experienced; meaning that the visual complexity and the more demanding task had no impact on the user's BCI performance. (v) Finally, and most importantly, the use of a secondary motor task (multi-tasking with the joystick) did not deteriorate the BCI performance at all. These findings conclude that our chosen approach is a suitable multi-modal or hybrid BCI implementation, in which the user can even do other tasks in parallel.

Different to other BCI-VR setups our current approach needed only a very short BCI training time and no classifier adaptation was necessary while changing the visual scenes. Despite watching movements in VE, motor imagery and its classification in the ongoing EEG was still possible without performance degradation. The integration of the BCI controlled action into the game was more intuitive than in our previous works, since we used the imagination of a foot movement to jump. The triggering of the discrete action to make the fish jump allowed us in this approach to overcome the limitations of our previous works, where we always used a continuous control signal [21], [23], [25]. The continuous control approach led to frustration of the participants because of the high FN values in combination with high FP numbers, which did not occur with the paradigm in this experiment. On the contrary, the participants even reported that they liked the interaction, enjoyed the experience, found it more engaging, favored the curved conditions with the secondary task and preferred the BCI control method over the push-button condition in such game-like environments, independently of the level of performance. Generally in many experiments the subject is never or hardly ever rewarded for performing well with the BCI task. Our experiment, however, profits from the game as an attractive task, where the subject is motivated to get a higher score with a better BCI performance.

Especially the combination of peri-imagery ERD and post-imagery ERS features resulted in a good and stable online control signal for discrete events (the so called brain-switch [35]) in 50 % of the participants. The offline analysis of the EMG signal proved that only brain patterns were used for control. A combination of ERD and ERS based on support vector machines was already successfully demonstrated in simulations with offline data [45], where better TPR performances could be achieved compared to our online results in session 1, but equal to our offline results with optimized parameters. During the penguin runs, the TPR dropped slightly because a more critical jump timing was necessary, although the subjects did not rate it as more stressful. Not only did the penguin have to jump just before passing the fish, it also had to be at the correct height at the time to collect it. Therefore, the participants had to have the model of the game in mind, triggering the action ahead of time. Indeed, during the experiment such cases occurred where the penguin did jump but was still too low, which counted therefore as a "wrong" jump. Such BCI events would have been counted as correct detections in previous experimental designs. Our slightly worse FPR performance can be explained by our enlarged inter-trial pause times, leading to a period for FP detection of 10 s in our case instead of 6.5 s in the previous work [45].

We tried to start the experiments with simple tasks, gradually getting more and more demanding for the participants, especially since the penguin game required a more precise timing and is more challenging than the simple screen feedback. A slight learning effect is visible over the different runs with the penguin game within each condition. Nevertheless, the subjects achieved the same performances in both steering conditions. Furthermore, the introduction of the secondary joystick task required a split attention between the jumping and the steering (multi-tasking). In general, more fish were missed in these conditions, as the alignment of the penguin to jump in the proper direction is not always easy. Interestingly, and not expected, is the result that the six subjects performed slightly better (but not significantly) with the secondary task in the BCI condition compared to without the joystick. This was not the case for the manual push-button condition.

Summing up, we demonstrate that a hybrid BCI can be used to control a multi-modal and multi-tasking interaction without loss of BCI performance.

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Robert Leeb is a senior postdoctoral researcher at the Chair in Non-Invasive Brain-Machine Interface, Center for Neuroprosthetics at École Polytechnique Fédérale de Lausanne in Switzerland, where he works on the transfer of brain-computer interface (BCI) technology towards patient applications. He studied at Graz University of Technology, Austria, and Sheffield Hallam University, U.K., and received the M.Sc. degree in electrical and biomedical engineering, in 2000, from Graz University of Technology. In 2008, he received his Ph.D. in Computer Science from Graz University of Technology, Austria. His research interests include BCI systems, neuro-rehabilitation, biosignal processing, hybrid BCI approaches and virtual reality systems.

Marcel Lancelle researches in computer graphics, virtual reality, user interfaces and computer vision. He studied in Braunschweig, Germany and Grenoble, France and later worked at the HITLabNZ in Christchurch, New Zealand, at Graz University of Technology, at Fraunhofer Austria and most recently at Fraunhofer IDM@NTU in Singapore. He received his Ph.D. in 2011 from Graz University of Technology and his M.Sc. in 2004 from Technische Universität Braunschweig.

Vera Kaiser is research associate at the Institute of Knowledge Discovery at the Graz University of Technology since 2007. She received her Ph.D. in psychology from the University of Graz, Austria, in October 2012. Her research interests include basic research for brain-computer communication, brain-computer interface applications in patients, neurorehabilitation and neuronal correlates of cognitive processes.

Dieter W. Fellner is professor of computer science at TU Darmstadt, Germany and Director of the Fraunhofer Institute of Computer Graphics (IGD) at the same location. He is also professor at TU Graz, Austria, were he established the Institute of Computer Graphics and Knowledge Visualization. His research activities over the last years covered efficient rendering and visualization algorithms, generative and reconstructive modeling, virtual and augmented reality, graphical aspects of internet-based multimedia information systems and digital libraries.

Gert Pfurtscheller received his M.Sc. and Ph.D. degrees in Electrical Engineering from the Graz University of Technology, Graz, Austria. He was Full Professor of Medical Informatics and Professor of Brain Computer Interfaces at the Graz University of Technology (TUG), visiting Professor at Cape Town University and Vancouver University and is Emeritus Professor at TUG since October 2009. He was Head of the Institute of Biomedical Engineering, Director of the Ludwig Boltzmann Institute for Medical Informatics and Neuroinformatics and is Founding Director of the Brain-Computer Interface Laboratory (BCI-Lab) at the TUG. He has authored more than 300 publications in peer-reviewed journals and published 4 books. He was honoured by election as a member of the Austrian Academy of Science.