International Journal of Bioelectromagnetism
Vol. 9, No.4, pp. 237 - 244, 2007
www.ijbem.org

Self-paced exploration of the Austrian National Library through thought

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Abstract. The results of a self-paced Brain-Computer Interface (BCI) are presented which are based on the detection of senorimotor electroencephalogram rhythms during motor imagery. The participants were given the task of moving through a virtual model of the Austrian National Library by performing motor imagery. This work shows that five participants which were trained in a synchronous BCI could sucessfully perform the asynchronous experiment.

Keywords: Brain-Computer Interface, asynchronous, self-paced, motor imagery, navigation, virtual environment

1. Introduction

A Brain-Computer Interface (BCI) analyzes the brain activity and transforms the electroencephalographic (EEG) changes into control signals [Wolpaw et al., 2002]. Therewith it is possible to establish a direct communication channel between the human brain and a machine which does not require any motor activity. Different EEG signals can be used to as input to a BCI, either event-related potentials (ERPs), such as slow cortical potentials [Birbaumer et al., 2003], P300 potentials [Donchin et al., 2000] or SSVEP [Müller-Putz et al., 2005a], or transient oscillatory changes in the ongoing EEG [Pfurtscheller et al., 2001; Pfurtscheller et al., 2005; Wolpaw et al., 2002]. Up to now most BCI's operate in a cue-based or synchronous manner, in which the BCI system presents a cue and the subject performs a mental task after this cue [Guger et al., 2001]. The EEG signals are analyzed and used for control only in a predefined time window after the cue. By contrast, an asynchronous or self-paced BCI is constantly analyzing and classifying the ongoing EEG activity [Mason et al., 2000; Scherer et al., 2007]. In addition to detecting the intentional motor imagery tasks (MI) the system should also be able to detect if the user does not wish to generate a control command (non-control state, NC). In contrast to a synchronous BCI where the performance may be stated in terms of e.g. the classification accuracy, the performance of a self-paced BCI is difficult to evaluate. For computing performance rates, it is necessary to access the subjects "real" intent and to compare it to the BCI output. Unfortunately, this information is not directly accessible. So either (i) the user is immediately reporting whether a command or control signal occurred correctly or not [Borisoff et al., 2006] or (ii) the task given to the subject requires activity periods (MI states) and pause times (NC states) and the successful accomplishment of the task can be used as the performance measure [Leeb et al., 2007a; Scherer et al., 2007]. Such an approach with defined activity and pause times is termed "experimenter-cued asynchronous BCI." Therefore, in this study an experiment with such requirements was designed within a virtual environment (VE). The use of a VE ensured that the subject was motivated to perform the experiment and that these activity and pause periods could be incorporated into the goal of the task. Therefore the participant was placed in a multi-projection-based stereo VE system called "DAVE" [Fellner et al., 2003]. The participants had the task of moving through a virtual model of the Austrian National Library by performing motor imagery.

2. Material and Methods

2.1 The system

In order to carry out the experiments two different and complex systems had to be integrated: the BCI and the DAVE (Definitely Affordable Virtual Environment); see Figure 1. Both systems run on two different machines (hardware) and different platforms (software).

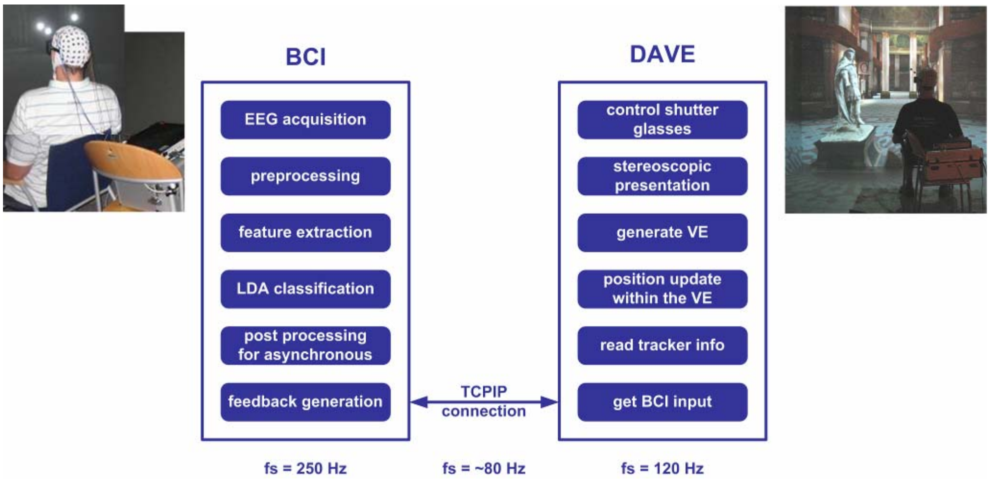


Figure 1. *System diagram of the hardware setup. The BCI system on the left analysis the EEG signals and the extracted control commands were transferred into movements with the VE projected in the DAVE system.*

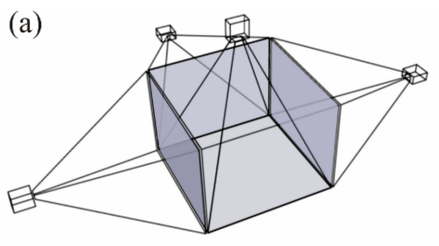
A BCI-system is, in general, composed of the following components: Signal acquisition, preprocessing, feature extraction, classification (detection), post processing and application interface (left side of Figure 1). The signal acquisition component is responsible for recording the electrophysiological signals and providing the input to the BCI. Preprocessing includes, artifact reduction (electrooculogram (EOG) and electromyogram (EMG)), application of signal processing methods, i.e. low-pass and / or high-pass filter, methods to remove the influence of the line-frequency and in the use of spatial filters (bipolar, Laplacian, common average reference). After preprocessing, the signal is subjected to the feature extraction algorithm. The goal of this component is to find a suitable representation (signal features) of the electrophysiological data that simplifies the subsequent classification or detection of specific brain patterns. There are a variety of feature extraction methods used in BCI systems; a non exhaustive list of these methods includes amplitude measures, band power, Hjorth parameters, autoregressive parameters and wavelets. The task of the classifier component is to use the signal features provided by the feature extractor to assign the recorded samples of the signal to a category of brain patterns. In the simplest form, detection of a single brain pattern is sufficient. This can be achieved by using a threshold method. More sophisticated classifications of different patterns depend on linear or nonlinear classifiers. Post-processing issues such as dwell time (time in a certain state before an event occurs), refractory period (time after an event), combination of classifier and time dependent modeling uses the pre-knowledge of the actual experiment to adapt the classifier output to the current experiment. In the case of an asynchronous or self-paced BCI not only between the different intentional motor imagery tasks but also the non-control state has to be identified. No output should be generated while detecting the NC state and control commands during the MI tasks. The final output of the BCI, which can be a simple on-off signal or a signal that encodes a number of different classes, is transformed into an appropriate signal that can then be used to control a VE system.

The used Graz-BCI system [Pfurtscheller et al., 2007] consisted of one biosignal amplifier (g.tec, Guger Technologies OEG, Graz, Austria), one data acquisition cards (E-Series, National Instruments Corporation, Austin, USA) and a standard personal computer running Windows XP operating system (Microsoft Corporation, Redmond, USA). The recording was handled by rtsBCI, 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 (http://biosig.sf.net). The EEG signals were sampled and processed with a sampling frequency of fs = 250 Hz.

The DAVE (right side of Figure 1) is a surround projection system which consists of three rear-projected active stereo screens (left, right and front wall on that the images are projected from outside) and a front-projected screen on the floor (image for the floor is projected from above). It generates three-dimensional stereoscopic representations of computer animated worlds [Fellner et al., 2003]. The installation itself is a cubicle with 3.30 m wide walls (see Figure 2a). For each of the projection screens double DLP projectors (Cube3D[2] projectors with resolution of 1400 x 1050 from Digital Image (Overath, Germany)) are alternating projecting the images for the right and left eyes on the respective wall: ...RLRLRL..., displayed with 60 Hz each (see Figure 2b). In order to separate the displayed images the observer needs to wear so-called shutter glasses that, quickly changing, blacken the view for one of the eyes at every given moment, in exact synchronization with the projectors.

The projections on the screens are continuously adapted to the movements of the visitor by re-computing the projected images for the respective current viewing position and direction (update rate of 30-50 times per second). Thereby, the position of the subject is determined using four infrared cameras that keep track of a number of highly retro-reflective balls that are attached to the shutter glasses. This makes it possible to compute images for every screen that accurately fit the visitor's view on the simulated scene. It is vital that the images from different screens meet seamlessly at the common border. The projectors are fed by 8 render clients, reasonably powerful off-the-shelf Linux-PCs equipped with the latest high-end graphics boards. Rendering is coordinated by the DAVE server.

The VE presented was a model of the Austrian National Library (see Figure 3). It was modeled in Maya and 3D Studio (both from Autodesk Inc., San Rafael, CA, USA), but the statue was built using a photogrammetric 3D reconstruction (VRVis Research Center for Virtual Reality and Visualization, Ltd., Vienna, Austria). In total approximately 120.000 faces and 60.000 vertices together with 30MB of texture were necessary to create such a photo-realistic model of the 80 meter long and 14 meter wide main hall (center area 25 meter wide, see Figure 4) [Sormann et al., 2005; Settgast et al., 2007]. The VE application was implemented using the scene graph library OpenSG (http://www.opensg.org). This software library hides away the complexity of developing software for a synchronized distributed system of nine computers behind a concise interface and ensures that all clients are provided with up-to-date observer coordinates and that they render the common 3D scene at the same time.



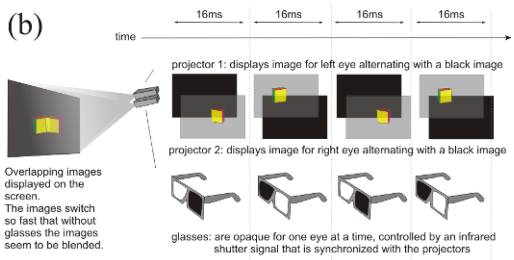


Figure 2. *(a) Physical Dave installation with indicated projection screens and (b) principle of time interlaced projections with shutter glasses so that each eye gets a different image..*

In all experiments the subjects were sitting in a comfortable chair in the middle of the DAVE (see Figure 3). An electrode cap (Easycap, Germany) was fitted to the subject’s head, and seven Ag/AgCl electrodes were mounted over the sensorimotor cortex, either as three bipolar (electrodes located 2.5 cm anterior and posterior to C3, Cz and C4, respectively, according to the international 10-20 system [Jasper, 1958]) or as one Laplacian channel (over C3 or C4). The ground electrode was positioned on the forehead (position Fz). The EEG was amplified (sensitivity was set to 50 µV for bipolar derivations and 100 µV for Laplacian derivation; power-line notch filter was activated) and band pass filtered between 0.5 and 100 Hz (EEG acquisition and preprocessing block, see Figure 1). From these recordings logarithmic band power features (Butterworth IIR filter of order 5) were calculated sample-by-sample for 1-sec windows (feature extraction, see Figure 1) and classified with a linear discriminant analysis (LDA classification, see Figure 1) (further details about the Graz-BCI see [Pfurtscheller et al., 2007]). The post processing generated a control signal only when the LDA output of the specified MI was exceeding a selected threshold for a predefined dwell time [Townsend et al., 2004]. The detected events were transferred into control commands for the VE on a sample-by-sample basis of 250 Hz.

Figure 3. *Participant with electrode cap sitting in the DAVE inside a virtual model of the main hall of the Austrian National Library.*

The DAVE system was connected to the BCI system via a wireless TCPIP connection (see Figure 1). Approximately 80 times per second the DAVE requested the current BCI output. Thereby relative coordinate changes (Δspeed and Δrotation) were transmitted. Together with the current position of the subject within the VE and the tracking information of the subject's head (physical movements) the new position within the virtual world was calculated. Nevertheless the visual presentation of the scene was rendered with 120Hz (60 Hz for each eye). The whole procedure resulted in a smart forward movement through the virtual library whenever the BCI detected the specified MI.

2.2 The Experiment

Five subjects participated in this experiment. All subject started with a synchronous BCI training (two MI classes). During this training they learned to establish two different brain patterns by imagining hand or foot movements (for details see [Müller-Putz et al., 2007; Leeb et al., 2007b]). The frequency bands for the logarithmic band power features were individually adapted for each subject [Pfurtscheller et al., 2007] and are given in Table 1. After offline LDA output analysis, the MI which was not preferred (biased) by the LDA was selected for self-paced training (see Table 1). Each time the LDA output was exceeding a selected threshold (Th in Table 1) for a predefined dwell time (Tdwell in Table 1) the BCI replied the DAVE request with a move command (speed = 1.5 m/s and rotation = 0.9°/s).

The task of the subject within the VE was to move through motor imagery towards the end of the main hall of the Austrian National Library along a predefined pathway (see Figure 4). The reason for the curved path was the location of the two marble column rows and the position of the statue. The starting point was at the entrance door and the subject had to stop at five specific points indicated in Figure 4 (entrance, column row, statue, column row and exit). After a variable pause time (between 20-95 seconds) the experimenter gave a command and subject started to move as fast as possible towards the next point.

Table 1. *Type of EEG recording, used MI type, the frequency bands of the logarithmic band power, the used threshold values (Th) and the dwell time (Tdwell) are given for each subject.*

subject	*EEG-derivation*	*async.MI*	*f [Hz]*	*Th*	*Tdwell [s]*
al4	lap C4	left hand	11-15	0.1	1.0
			24-26		
al9	lap C3	right hand	9-13	1	2.0
			15-17		
			20-25		
al10	lap C3	left hand	9-13	0.5	1.5
			21-24		
x20	bipolar	right hand	8-12 (C3)	0.5	1.2
			24-30 (C4)		
x21	bipolar	left hand	8-12 (C3)	0.1	1.0
			23-27 (C3)		
			12-14 (C4)		
			24-28 (C4)		

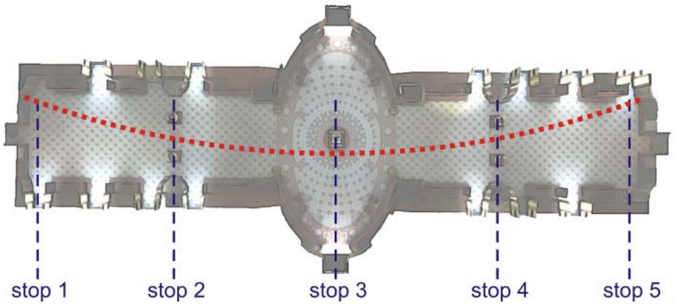


Figure 4. *Layout of the main hall of the library. Dotted lines shows the predefined pathway and dashed lines the five stopping points (entrance, column row, statue, column row, exit).*

Each subject performed six runs, in which the BCI was constantly analyzing the EEG activity and MI and NC tasks were detected continuously (asynchronously), but the task itself was cued by the experimenter. The initiation to move forwards was given by the experimenter (verbal cue, synchronous event), but the time necessary to move to the next specific stopping point depended only on the performance of the subject (asynchronous task). The duration of the pause time was given by the experimenter, but the activity within the pause was controlled by the subject. The reason for the experimental design chosen was that in case of an asynchronous or self-paced BCI the performance evaluation is not as easy as in case of a synchronous one. In this experiment, defined periods of moving (activity time) and periods of pausing (pause time) existed. For a perfect performance no MI and therefore no movement should be detected during the pause time, and during the activity time only MI should be detected. Additionally, the time necessary for accomplishing the task should be as short as possible. Therefore such an approach with defined activity and pause times is termed “experimenter-cued asynchronous BCI.”

Periods of true positives (TP, correct moving) and false negatives (FN, periods of no movement during activity time), as well as false positives (FP, movements during the pause time) and true negatives (TN, correct stopping during pause time) were identified (see Figure 5). The true positives rates (TPR) and false positive rates (FPR) were calculated as:

$$TPR = \frac{TP}{TP + FN} \cdot 100 \, [\%] \qquad FPR = \frac{FP}{TN + FP} \cdot 100 \, [\%]$$

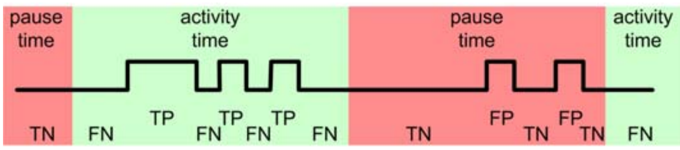


Figure 5. *Definition of TP, FP, TN, FN during activity and pause time.*

Following setups were performed in each experiment session:

- Electrode montage (Laplacian or bipolar)
- Check of the EEG quality (via BCI-scope)
- One synchronous BCI run (basket game, [Krausz et al., 2003])
- Update of the LDA-bias if necessary (preferred / biased to one class?)
- One asynchronous jump-and-run game run [Müller-Putz et al., 2007]
- Update of threshold (for asynchronous detection)
- Six DAVE runs (moving through thought)

3. Results

The online performance of the first run of subject al10 is given in detail in Figure 6. In this run the subject needed 226 seconds to reach the end of the main hall, whereby the duration of the pause times at the stopping points were 33.5, 30.5, 29.6 and 32.8 seconds. An additional pause before the first move instruction (3.7 seconds) and after reaching the end of the hall (6.9 seconds) existed. This resulted in a TPR of 50.11% and FPR of 5.84%. Each subject performed six runs in the virtual library. The averaged performance (TPR and FPR rates) and the duration of the activity and pause time are given in Table 2. Every run had a different duration, caused on the one hand by the varying pause time given by the experimenter (sum is given in Table 2) and on the other hand on the moving performance of the subject itself. For some subjects it was very easy to increase the LDA output over the threshold (MI detected) and for others the threshold was slightly too high and therefore not so many MI's could be detected which resulted in longer runs. In general all subjects had to move down the total way of the VE, so the same amount of MI time was necessary, only the ratio between MI and NC during activity time was different.

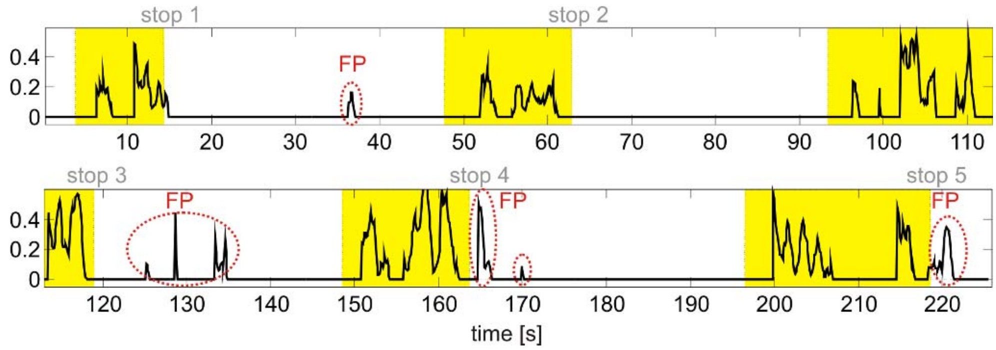


Figure 6. *Online performance of the first run of subject al10. The yellow rectangles mark the periods when the subject should move to the next point. The black line is the actual BCI output after the postprocessing. Whenever the line is not zero a movement occurred. Periods of FP are indicated with red dotted circles.*

Table 2. *The averaged performance of the navigation task (TPR and FPR), the activity (Tactivity) and the pause time (Tpause) of all 6 runs are given (note: * data of two runs were lost).*

subject	*TPR [%]*	*FPR [%]*	*Tactivity [s]*	*Tpause [s]*
al4	14.3	2.0	1511	795
al9	17.0	7.1	1219	1081
al10	50.0	4.0	506	885
x20*	13.9	5.8	1025	636
x21	20.8	1.8	1184	1128

4. Discussion & Conclusion

In this experiment, a successful application of the Graz-BCI in an asynchronous or self-paced moving experiment with a small number of EEG recordings could be demonstrated. Five subjects were able to accomplish the task to move through the virtual model of the Austrian National Library by motor imagery. Only a small number of FPR (between 1.8 – 7.1 %) occurred in the experiments. Especially the results of al10 and x21 are encouraging. The numbers of TPR and FPR in relation to the activity and pause time show that there is still space for improvement. A challenge is to optimize the threshold and the dwell time to distinguish between MI and NC states, and thereby to improve TPR and FPR. The usage of a virtual environment created an interesting, challenging and highly visual appealingly task which ensured that the participants were highly motivated and tried to perform their best. Motivation is a very crucial point in such experiments.

One disadvantage of the experimental strategy applied was that the subjects had to perform the motor imagery over a very long period. In the example given in Figure 6 the subjects activity time was between 10.5 and 25.6 seconds. Unfortunately oscillatory EEG components need some time to appear and disappear, and subjects are unable to produce changes in oscillatory activity for extended periods of time. Therefore, the reported FN numbers are very high due to this task definition. Nevertheless it is much more import to decrease the FPs than to decrease the FNs. In a real-world situation it would be crucial that the BCI does not spuriously detect an event (FP), but it is not so critical if the subject has to imagine something more than once (FN) before the BCI detects it.

Perhaps in future experiments a different strategy should be used. The BCI could be used to switch the moving on and off, instead of continuing the MI during the movement period. So every time the BCI detects the MI, the status will be toggled. It is currently unknown if the toggling would be manageable and practical for the subject, especially if distinct stops must be achieved at specified points. Another different strategy would be to use every detected MI event to trigger one footstep (additional with a refractory period [Townsend et al., 2004]). This would result in several steps, but not in a continuous movement. A disadvantage of such a strategy would be that the subject could only move or stop on a grid basis, however shorter bursts of imagery could be used.

Unlike other asynchronous BCI experiments, long pause times have been used in these experiments. Pause times of up to one and a half minutes are not often used. Some works previously reported had a pause time of up to only 5 seconds [Zhang et al., 2007], up to 7 seconds [Bashashati et al., 2006], up to 8 seconds [Borisoff et al., 2004], up to 10 ± 8 seconds [Müller-Putz et al., 2005b], up to 17 seconds [Scherer et al., 2007] or no pause at all [Millan et al., 2003; Müller et al., 2006]. In the work of Bashashati et al. [2006], they described the use of a NC recording of 2 minutes, but did not present any detection results. The pause time and therefore the NC state is the most important part in an asynchronous or self-paced BCI. The community already showed that it is possible to detect the MI tasks, but the ability to correctly detect the absence of MI over a long period is still an ongoing issue. Patients will be using the BCI for hours or even longer and most of the time they don't want to perform anything. They will only choose to select an operation or perform a task in very short periods, but most of the time the BCI should be idling. Therefore, the pause times used in these experiments are also much too short for real-world applications; however it was an important step in the correct direction.

Acknowledgements

This work was carried out as part of the PRESENCCIA project, an EU funded Integrated Project under the IST program (Project no. 27731), the EU COST Action BM0601: Neuromath and Wings for Life – Spinal Cord Research Foundation, project 002/06. The authors are grateful to George Townsend for proof-reading the manuscript.

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