Playing Tetris with Non-Invasive BCI

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***Abstract*—This paper presents a non-invasive Brain Computer Interface (BCI) game that is inspired on the Tetris game. The BCI-Tetris is presented in three different versions. Two versions based on the P300 event related potential (ERP), and one version that combines the P300 ERP with the control of sensorimotor rhythms. The BCI-Tetris is being developed to be tested in pilot experiments with children with attention-deficit and hyperactivity disorder (ADHD). The results reported in this study with able-bodied participants show that the BCI-Tetris can be effectively controlled.**

***Keywords*-Games; BCI; P300; Motor imagery; ADHD;**

I. Introduction

Non-invasive Brain Computer Interfaces (BCIs) use electroencephalographic (EEG) signals to control systems without recurring to the motor output pathways. Most of the BCIs developed until now have been designed as a communication system for people who suffer from severe motor impairments such as amyotrophic lateral sclerosis, muscular dystrophy, spinal cord injuries and cerebral palsy. For these individuals, EEG is a new communication channel that can significantly improve their interaction with the world. Farwell and Donchin developed in the eighties a BCI paradigm that allows to write by successively selecting letters of the alphabet [1]. This speller has been used worldwide achieving successful results in both able-bodied and motor disabled individuals [2], [3], [1]. Recently, many other BCI applications have emerged, namely the control of prosthetic devices, control of wheelchairs [4] [5] and game control [6]. A major research area closely related to BCI is the neurofeedback, i.e., the real-time feedback of brain activity. Neurofeedback has been used in game applications for the treatment of children and adolescents with attention-deficit and hyperactivity disorder (ADHD) and for the treatment of seizure disorders [7], and also in neuro-rehabilitation for recovery from incidents of stroke and traumatic brain injury [8].

In this paper we describe the development of 3 different versions of a Tetris-like game, based on the P300 event related potential (ERP) and based on the control of sensorimotor rhythms. P300 is elicited by a target event of an oddball paradigm [1]. It is characterized by a positive peak that occurs about 300 ms after the onset of the target event (a random and rare stimulus among frequent non-target stimuli). The μ (8-12 Hz) and β (18-24 Hz) waves are sensorimotor rhythms that decrease during motor imagery and increase during motor relaxation [9]. This increase and decrease are known as event related synchronization and desynchronization (ERS/ERD). The proposed BCI-Tetris intends to be used in pilot experiments with children with ADHD. In the context of ADHD, P300 has been used only as a neurophysiologic marker of ADHD or to assess the improvements of patients after the treatment. For the best of our knowledge, the use of P300-based BCIs for the treatment of ADHD has never been researched before. P300 is an endogenous ERP that depends on selective attention, therefore we can hypothesize that continuous sessions of tasks based on P300 can improve the attention levels of players. The combination of P300 ERP and sensorimotor control, the latter typically used in neurofeedback applications, can be an interesting approach to be tested clinically. This paper, however, is only a proof-of-concept showing that BCI-Tetris can effectively be controlled.

II. EEG-based games: related work

There are several types of neural mechanisms that can be used to control a game with EEG, namely neurofeedback based on several EEG rhythms, P300 event related potentials (ERP), and steady-state visual evoked potentials. Some research works using these neural mechanisms are presented in the following (see [6] for a more formal survey). In clinical applications, neurofeedback is frequently used in the form of game control. Games give an additional motivation to the trainees [10], which is of particular relevance for children. One of the main applications of neurofeedback is on the treatment of ADHD, and it is considered today an effective alternative to pharmacologic treatments. ADHD show an elevated relative theta power, reduced relative alpha and beta power, and elevated theta/alpha and theta/beta power ratios [7]. This information can be used to induce the regulation of these rhythms through EEG feedback training (reinforcement or inhibition). The ability of subjects to manipulate the μ and β sensorimotor rhythms (oscillations recorded over the motor cortex) has also been used to control several types of games that go from three-dimensional (3D) video games to simple 2D games. For example, in [11] several participants learned to steer a person in a 3D game. The results showed that subjects could gain very good binary control of μ rhythms after approximately 10 h of training. Also, in [12] the authors used sensorimotor rhythms to control a pinball machine. In [13], the authors proposed a 2D and a 3D game controlled by the level of attention. The algorithms use a fractal dimension model to extract features from the EEG activity. In the first game, a ”Dancing Robot”, the player has to control the speed of the 3D robot while the robot is dancing. The dancing speed depends on the concentration level of the player. In the second game, ”Brain Chi”, the player helps a 2D little boy to fight against evil bats. In the same sense, the size of protection ball depends on the player concentration level.

While in the above approaches, the user controls the games based on induced activations of EEG rhythms, meaning that the user can initiate actions without depending on stimuli from the game, there are other game approaches relying on external stimuli. Steady-state visual evoked potentials (SSVEP) is an oscillatory rhythm that appears in the visual cortex as a response to a stimulus flickering at a constant frequency. The authors in [14] use SSVEP in a game where the player has to focus and gaze to one of two possible checkerboards flickering at different frequencies. The objective is to gain balance control (1D) of a character on a tightrope. Following the same neuromechanism, Martinez *et al.* [15] propose a 2D racing game with four different checkerboards around a car (which represent 4 different directional controls) flickering at different frequencies. SSVEP is an exogenous potential and therefore it is mainly dependent on the type of the stimulus. It does not require training of the players, however the flickering effect usually causes eyestrain, limiting the time of use. Finally, P300 ERP is also an approach to control games by following oddball paradigms. Piccione et al. [16] proposed a P300-based game, where the participants are asked to control the movement of a virtual object (a blue ball) along a path specified by the examiner. Four arrows are randomly flashed in peripheral positions of the monitor corresponding to the four possible directions that control the ball. In [17], a ”MindGame” inspired in the original P300 row-column speller paradigm is played on a checkerboard-styled game board with 28/18 fields and 12 randomly positioned trees. The fields with the trees are potential targets in an oddball paradigm and thus the player’s task is to move the character from tree to tree.

III. Tetris-games approaches

The proposed games consist on three different approaches based on the Tetris game. The original game suffered several simplifications and adaptations to allow its effective control using the proposed neuromechanisms. The Tetris board layout is presented in Fig. 1. Two versions, V1 and V2, are fully based on the P300 paradigm, and a version V3 combines the

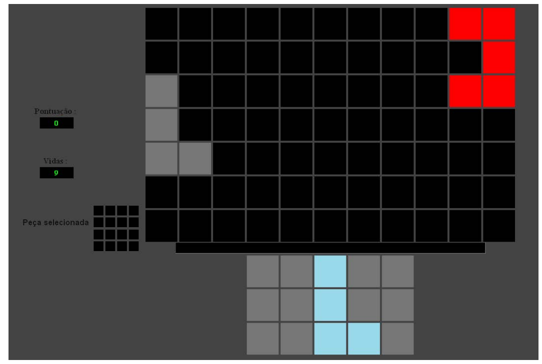

Figure 1. Game board of the P300-based Tetris. The target piece to be selected is indicated at the bottom of the board. To help the player, the position where the piece is flashed appears in gray. The red piece is one of the pieces being flashed at the screenshot time.

P300 paradigm of V2 with a motor imagery paradigm. At this stage, the implementation of Tetris V3 still has these two parts separately. Each one of the three approaches has two sub-versions of the game, a calibration/training version and an online version where the user effectively plays.

1) Tetris V1 - P300-based: In Tetris V1, there are 16 combinations comprising different positions and rotations of four different pieces as represented in Fig. 2Left). The goal is to select the target piece that is placed in the bottom of the board (see Fig. 1). There are four pieces each one with four possibilities of rotation. The resulting 16 combinations take a fixed position in the Tetris layout. The pieces flash randomly, but at each instant only one piece is visible. The piece remains flashed during 100 ms, and the stimulus onset asynchrony (SOA - interval between the onset of two consecutive stimuli) is 200 ms. It is supposed that the target piece elicits a P300 ERP. Since there are 16 pieces, the target event has a probability of 1/16. To increase the events perception, each piece has a different color. Moreover, to facilitate the task of finding the position of the target piece, this one is indicated in gray in its flashing position.

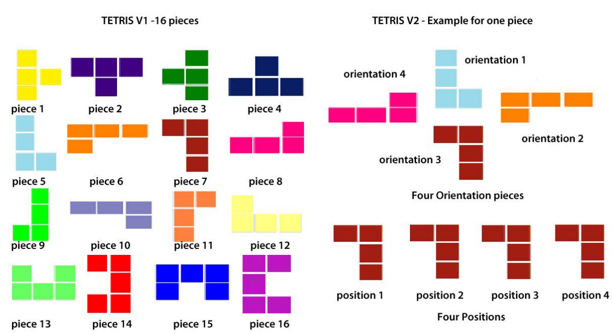

Figure 2. Pieces used in Tetris games. Left) Version V1 with 16 combinations of 4 pieces, combining simultaneously position and orientation; Right) Version V2. Example of one piece showing the four possible positions along the horizontal axis and the four possible rotations.

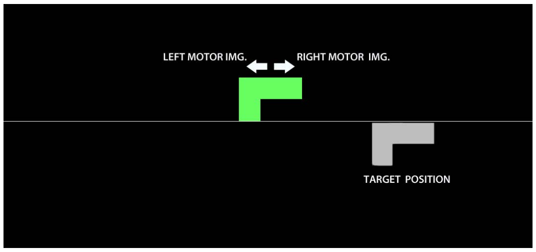

Figure 3. Layout of the Tetris board in motor imagery. Movement of the piece for left or right is continuous along the horizontal axis.

2) Tetris V2 - P300-based: The Tetris V2 has an operation more approximated to the original Tetris game. There are four possibilities for rotation and four possibilities for position, respectively. In the first instance, the user selects the desired rotation and thereafter he selects the desired position along the horizontal axis. Thus, the user has to choose a target among four possibilities, which means that each target event has a probability of 1/4. The pieces are randomly flashed with a flash time of 100 ms and a SOA of 200 ms. If the user fails to select the correct rotation, he is unable to detect the correct target even if he selects correctly the position. The target piece is at the bottom of the board, and also in gray in its flashing position .

3) Tetris V3 - Hybrid P300/motor Imagery: The Tetris V3 is an hybrid approach that combines two parts, one controlled by the P300 and the other controlled by motor imagery. This version is very close to the original Tetris. The rotation of the piece is selected the same way as in Tetris V2, and the position of the piece is selected through motor imagery. The Tetris board during motor imagery is slightly different from the one in P300 (see Fig. 3). The user has to move the piece until the correct position is reached (1D movement). It is possible to select two mental approaches to move the piece to left or right, namely, imagination of left vs. right motor tasks, or motor imagination vs. rest (relaxation state). A motor imagination moves the piece to one of the pre-defined directions. Moreover, to adjust the difficulty of the game to the skills of the player, the precision of the horizontal position can be adjusted from fine to coarse, and the time to achieve the position can also be adjusted.

IV. Methods

A. Participants and data acquisition

Despite many participants tested the proposed paradigms, only two of them made systematic experiments. Therefore, this study only reports the experiments made with 2 able-bodied participants. The EEG activity was acquired with a g.tec gUSBamp amplifier. Signals were recorded from 12 Ag/Cl electrodes at positions Fz, Cz, C3, C4, CPz, Pz, P3, P4, PO7, PO8, POz and Oz of the international extended 10-20 standard system with a g.tec cap. The electrodes were referenced to the right or left ear lobe and the ground was placed at AFz. Signals were sampled at 256 Hz, and filtered by a 0.1-30 Hz bandpass filter and a 50 Hz notch filter. The electrodes impedance varied from subject to subject, but were almost always kept under $10K\Omega$.

B. Classification

The classification models were obtained from the datasets gathered in the calibration/training sessions that preceded the online sessions. Two different classifiers were chosen for the P300 and motor imagery approaches.

1) P300: The offline and online classification was performed following the methodology that we presented in [2]. It uses a statistical spatial filter that cascades a Fisher beamformer and a Max-SNR beamformer (C-FMS). The twelve input channels are transformed into two high SNR (signal-to-noise ratio) projections, which are then fed to a naïve Bayes classifier (NB). The spatial filter is applied to the average of the epochs collected from the repetitions of the same event. The spatial filter and classification models were obtained for each participant from the calibration data. The online detection of the symbol was made by choosing the event with the highest score returned from classification.

2) Motor imagery: Taking the μ and β band powers as features for left imagery vs. right imagery and imagery vs. rest, two classifiers were modeled following the well-known two-class Fisher linear discriminant (FLD). The goal is to maximize the intercluster distance between the two classes and minimize the intracluster within a given class in the new dimension space [18]. Let the within scatter matrix be defined as:

$$S_W = S_1 + S_2 \tag{1}$$

where S_1 and S_2 are the scatter matrices:

$$S_i = \sum_{x \in H_i} (x - m_i)(x - m_i)^T \quad , i = 1, 2 \tag{2}$$

The between scatter-matrix is defined as:

$$S_B = \sum_{i=1}^{2} (m - m_i)(m - m_i)^T \tag{3}$$

where $\mathrm{x} = (x_1|x_2|\cdots|x_n)$ is the vector with all x_i $d-$dimensional features (training vectors), m_i is the mean of the samples in class i, and m is the mean of all samples. For the new feature vector $\mathrm{y} = \mathrm{W}^T\mathrm{x}$, then $\hat{W}$ is given by:

$$\hat{W} = S_{\mathrm{W}}^{-1}(\mathrm{m}_1 - \mathrm{m}_2) \tag{4}$$

C. System framework

The recording and processing of EEG data is implemented on a real-time Simulink® environment controlled by an acquisition driver that provides a hard real-time clock (gUSBamp) [19]. However, the graphical part of Tetris is developed externally to Simulink, based on the Tcl/Tk high level language. Fig. 4 shows the system framework. The data communication interface between Simulink and the Tcl/Tk

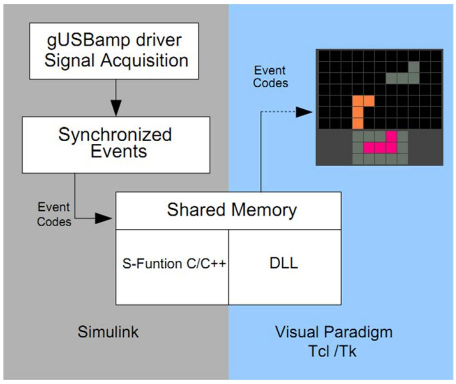

Figure 4. System framework. Event control is made in Simulink and then the event codes are sent to an external application built in TCL/TK through a shared-memory interface.

application is made through a shared memory driver. The driver was created with a C++ S-function on the Simulink side and using a DLL on the side of the external application. The DLL was generated by SWIG [20], a software development tool that simplifies the task of interfacing different languages to C and C++ programs. In a nutshell, SWIG is a compiler that takes C declarations and creates the wrappers needed to access those declarations from other languages including Tcl in our case. This framework allows a rapid development of signal processing algorithms, and at the same time an easy way to develop 2D or 3D games. The EEG acquisition, signal processing and events control are all performed in Simulink. In the P300-based versions of Tetris, Simulink sends the codes associated to the events and sends the detected target when a selection is made. In the motor imagery Tetris, Simulink sends the visual cues (in training sessions) and the detected position of the piece (online game).

D. Experimental procedure of calibration/training

1) P300: Before the online control of Tetris V1 and V2, each participant performed a calibration session. Each participant was instructed to be relaxed and attend the desired target, mentally counting the number of intensifications of the target. Participants were seated on a standard chair at about 60-70 cm of a 15” computer screen. In Tetris V1, each trial of the calibration session consisted of a round of 10 flashes for each Tetris piece. In Tetris V2, each trial consisted of a round of 5 flashes for each Tetris piece. The interval between trials (ITI, inter-trial interval) was settled to 3 seconds to allow the user to switch the attention focus to a new target piece. At the end of the calibration phase, the data set of Tetris V1 was composed of 120 target epochs and 1800 non-target epochs, while in Tetris V2, it was composed of 90 target epochs and 270 non-target epochs. An epoch is the data segment associated to each event which in our case has a duration of 1 second.

The online sessions occurred following the same protocols. The player receives as feedback the detected piece, indicating whether it was correctly or wrongly detected. In both online versions, the players are encouraged and stimulated with the score and the level of the game and even with written messages. The level of the game depends on the number of repetitions to detect the piece. A fewer number of repetitions increases the level of difficulty to detect the correct target.

2) Motor imagery: A training session of motor imagery preceded the online game. The training was performed according to the widely used protocol described in [9]. The procedure allowed the acquisition of data from left motor imagery, right motor imagery, and rest. During the training sessions, the participants were asked to not move and to keep the arms and hands relaxed. The participants had to start the imagination tasks according to the visual cues. Each participant made a training session of about 30 minutes, consisting on 100 trials of left motor imagery and 100 trials of right motor imagery. During the game played online, the player receives the cue to start, and then receives continuously the detected position of the piece (visual feedback).

V. Results

A. Offline classification results

1) P300 Tetris: The collected data sets were used to obtain the C-FMS spatial filter and the NB classifier. The classification error was measured by $\frac{FNR+FPR}{2}$, where FNR and FPR denote respectively false negative rate and false positive rate. This performance measure is more reliable than simple error rate because the target and non-target classes are highly unbalanced, and therefore the measure is not biased. Fig. 5 shows the classification error average over the two participants. To select a suitable number of event repetitions, the error rate was obtained for $K = 1 \cdots 7$ repetitions. For $K > 1$, the K epochs were averaged and the classification algorithms were applied to the average. Tetris is being designed to be operated by children in clinical applications, therefore it is important to minimize the number of channels to reduce the setup time. Several sets of channels are examined to compare the effect on classification performances. Four channel sets were selected. Channel set 1 comprises the 12 channels referred in section IV-A. Channel set 2 is composed of [Cz CPz Pz] channels, channel set 3 is composed of [P3 P4 CPz], and channel set 4 is composed of [PO7 POz PO8] channels. The results for Tetris V1 and V2 are respectively shown in the top and bottom of Fig. 5. Comparing the results of the two versions, the Tetris V1 show significative better results than Tetris V2. There are two factors that can explain this disparity. P300 amplitude is inversely proportional to target probability. In Tetris V1, the probability is 1/16 while in Tetris V2, the probability is 1/4. Therefore it is expected that paradigm of Tetris

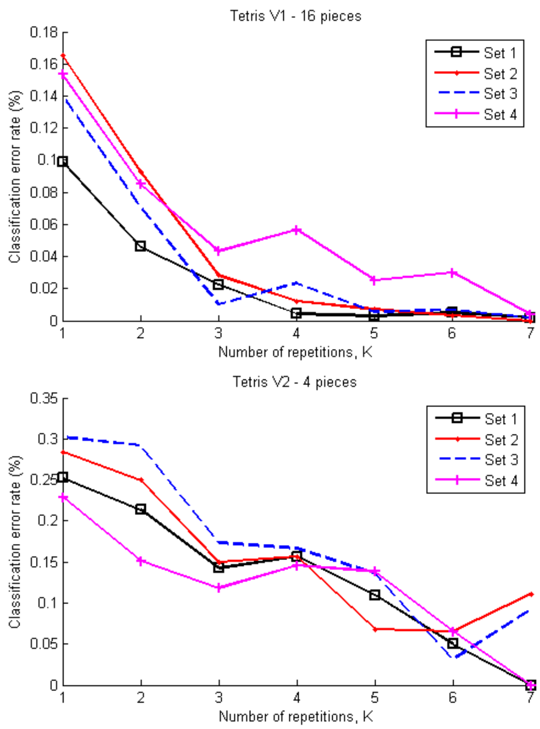

Figure 5. Classification results for $K = 1 \cdots 7$ event repetitions, taking different channels sets. Average of the two participants. Top: Tetris V1; Bottom: Tetris V2.

V1 elicits a P300 component with a larger amplitude. The second aspect concerns the number of target and non-target epochs. The larger number of training epochs in Tetris V1 may have benefit the robustness of its classifier. Comparing the different channel sets in Tetris V1, the performance of set 1 is higher than the the other sets, particularly for a small number of K repetitions. However, for $K \geq 3$ the error is inferior to 4%, for all sets except set 4. This indicates that a small number of channels can be used during clinical experiments. In Tetris V2, there are no significative differences between the channel sets. The non-superiority of set 1 relatively to the others may indicate that there is a high spatial variability of the P300 signal, and therefore the classification is not significantly improved by the C-FMS spatial filter.

2) Motor Imagery: Fig. 6 shows a frequency vs. time colormap representing the EEG rhythms, recorded at C3, during a left motor imagination of one of the participants. The visual cue was provided at instant 0 second. Before the visual cue, the subject was on rest. The desynchronization of μ (8-12 Hz) and β (18-24 Hz) is clearly visible during the motor imagination task, with emphasis for the rhythms μ. The power bands of μ and β rhythms recorded at C3 and C4 locations were the selected features to train the FLD classifier. Taking windows of one second of EEG, the averaged offline classification accuracy results were 70% for

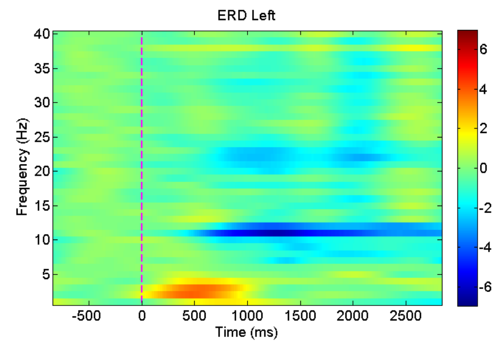

Figure 6. Frequency vs. time colormap of EEG recorded at C3 during a Left motor imagery task.

left vs. right imagery, and 75% for rest vs. motor imagery.

B. Online

The online experiments of Tetris V1 and V2 were performed after the calibration sessions, using the same protocol of the calibration phase. The number of repetitions was selected according to user performance. The online results are in Table I. The performance was superior in Tetris V1 than in Tetris V2, which is consistent with the offline results. In Tetris V2, most of the errors occurred on the selection of the horizontal position of the piece. This means that the rotation effect is more effective to elicit a P300 ERP than the effect of changing the position. This should be taken into consideration in further modifications of Tetris V2. In Tetris V1, the players were able to detect the target piece respectively with only 2 and 3 repetitions. In clinical applications, the level of difficulty can be incrementally adjusted to the skills of the players. The weaker results obtained with Tetris V2 may indicate that the approach has to be slightly changed.

In Tetris V3, the motor imagery protocol was significantly different from the training phase. After the piece was placed at the center, the user had 30 seconds to reach the target position. Both participants achieved successfully the target position within the 30 seconds on most of the trials. It should be emphasized that the control of sensorimotor rhythms require training. The two participants never had used a BCI before and performed the online sessions after only 30 minutes of training. Thus, it is expected that their skills increase with more training and that the time to achieve a target piece can be effectively shorter.

VI. Conclusion

This paper describes the development and the results of three different approaches to control a Tetris-like game. The results show that Tetris V1 is effectively controlled with a few number of event repetitions. Tetris V2 is more difficult to control which is mainly due to its high target probability. Since the player fails mainly on the selection of the position, then the integration of motor imagery to move the piece in

Table I
ONLINE CLASSIFICATION ACCURACY AFTER THE SELECTION OF 16 TETRIS PIECES USING DIFFERENT NUMBER OF REPETITIONS.

Participant	Repetitions	Tetris V1	Tetris V2
S1	6	-	62.5%
	5	100%	-
	3	100%	-
	2	87.5%	-
S2	6	-	62.5%
	5	100%	-
	3	75%	-

Tetris V3 is a suitable option. The sensorimotor rhythms showed to be effective on the control of the movement of the piece, and this control can be further improved after several training sessions. The BCI-Tetris was experimentally validated, but it is necessary now to receive the feedback of therapists and medical staff working with children with ADHD to make further improvements and adjustments.

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REFERENCES

[1] L. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event related brain potentials," *Electr. and Clin. Neuroph.*, vol. 70, no. 6, pp. 510–523, 1988.

[2] G. Pires, U. Nunes, and M. Castelo-Branco, "Statistical spatial filtering for a p300-based bci: Tests in able-bodied, and patients with cerebral palsy and amyotrophic lateral sclerosis," *J. of Neurosc. Methods*, vol. 195, no. 2, pp. 270 – 281, 2011.

[3] G. Townsend, B. LaPallo, C. Boulay, D. Krusienski, G. Frye, C. Hauser, N. Schwartz, T. Vaughan, J. Wolpaw, and E. Sellers, "A novel P300-based brain-computer interface stimulus presentation paradigm: Moving beyond rows and columns," *Clin. Neurophysiol.*, vol. 121, no. 7, pp. 1109 – 1120, 2010.

[4] B. Rebsamen, C. Guan, H. Zhang, C. Wang, C. Teo, M. Ang, and E. Burdet, "A brain controlled wheelchair to navigate in familiar environments," *IEEE Trans. on Neural Syst. and Rehab. Eng.*, vol. 18, no. 6, pp. 590–598, dec 2010.

[5] F. Galn, M. Nuttin, E. Lew, P. Ferrez, G. Vanacker, J. Philips, and J. del R. Milln, "A brain-actuated wheelchair: Asynchronous and non-invasive brain-computer interfaces for continuous control of robots," *Clin. Neurophys.*, vol. 119, no. 9, pp. 2159 – 2169, 2008.

[6] B. Reuderink, "Games and brain-computer interfaces: The state of the art," Centre for Telematics and Infor. Tech., University of Twente, Enschede, Tech. Rep. TR-CTIT-08-81, 2008.

[7] V. J. Monastra, S. Lynn, M. Linden, J. F. Lubar, J. Gruzelier, and T. J. LaVaque, "Electroencephalographic biofeedback in the treatment of attention-deficit/hyperactivity disorder," *Applied Psychophys. and Biofeedback*, vol. 30, pp. 95–114, 2005.

[8] J. C. Perry, J. Andureu, F. I. Cavallaro, J. F. Veneman, S. P. Carmien, and Keller, *Effective game use in neurorehabilitation: user-centered perspectives. In: Handbook of Research on Improving Learning and Motivation through Educational Games*. IGI Global, 2010.

[9] G. Pfurtscheller, N. Christa, A. Scholgl, and K. Lugger, "Separability of eeg signals recorded during right and left motor imagery using adaptive autoregressive parameters," *IEEE Trans. on Rehab. Eng.*, vol. 6, no. 3, pp. 316–324, 1998.

[10] A. Pope and O. Palsson, "Helping video games 'rewire our minds'," *NASA technical report*, 2004.

[11] J. Pineda, D. Silverman, A. Vankov, and J. Hestenes, "Learning to control brain rhythms: making a brain-computer interface possible," *IEEE Trans. on Neural Syst. and Rehab. Eng.*, vol. 11, no. 2, pp. 181 –184, 2003.

[12] M. Tangermann, M. Krauledat, K. Grzeska, M. Sagebaum, B. Blankertz, and K.-R. Muller, "Playing pinball with non-invasive bci," *Advances in Neural Information Process. Syst.*, vol. 21, 2008.

[13] Q. Wang, O. Sourina, and M. K. Nguyen, "Eeg-based "serious" games design for medical applications," in *Int. Conf. on Cyberworlds (CW)*, 2010, pp. 270 –276.

[14] E. Lalor, S. Kelly, and C. Finucane, "Steady-state vep-based brain-computer interface control in an immersive 3d gaming environment," *EURASIP J. on Applied Signal Process.*, no. 19, pp. 3156–3164, Jun. 2005.

[15] P. Martinez, H. Bakardjian, and A. Cichocki, "Fully online multicommand brain-computer interface with visual neurofeedback using ssvep paradigm," *Computational Intell. and Neurosc.*, jun 2007.

[16] F. Piccione, F. Giorgi, P. Tonin, K. Priftis, S. Giove, S. Silvoni, G. Palmas, and F. Beverina, "P300-based brain computer interface: Reliability and performance in healthy and paralysed participants," *Clin. Neurophysiol.*, vol. 117, no. 3, pp. 531 – 537, 2006.

[17] A. Finke, A. Lenhardt, and H. Ritter, "The mindgame: A p300-based brain-computer interface game," *Neural Networks*, vol. 22, no. 9, pp. 1329 – 1333, 2009.

[18] R. schalkoff, *Pattern Recognition, Statistical, Structural and Neural Approaches*. John Wiley & Sons, 1992.

[19] C. Guger, S. Daban, E. Sellers, C. Holzner, G. Krausz, R. Carabalona, F. Gramatica, and G. Edlinger, "How many people are able to control a p300-based brain-computer interface (bci)?" *Neurosc. Letters*, vol. 462, no. 1, pp. 94 – 98, 2009.

[20] "Simplified wrapper and interface generator-swig," http://www.swig.org/.