

## A P300-based EEG-BCI for Spatial Navigation Control

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**Abstract**— In this study, a Brain Computer Interface (BCI) based on the P300 oddball paradigm has been developed for spatial navigation control in virtual environments. Functionality and efficacy of the system were analyzed with results from nine healthy volunteers. Each participant was asked to gaze at an individual target in a 3x3 P300 matrix containing different symbolic navigational icons while EEG signals were collected. Resulting ERPs were processed online and classification commands were executed to control spatial movements within the MazeSuite virtual environment and presented to the user online during an experiment. Subjects demonstrated on average, ~89% online accuracy for simple mazes and ~82% online accuracy in longer more complex mazes. Results suggest that this BCI setup enables guided free-form navigation in virtual 3D environments.

### I. INTRODUCTION

Brain Computer Interface (BCI) systems translate brain-derived non-muscular signals into new pathways of communication and control [1]. These new mechanisms provide a direct channel from brain activity to action, acting as a potential alternative to neuromuscular control in cases where such routes are compromised, or serving in a supplementary nature for healthy individuals. BCI research efforts principally focus on the restoration of communication for patients suffering from crippling neuromuscular diseases such as amyotrophic lateral sclerosis (ALS), and neuroprosthetic control in amputees and spinal cord injury victims. However BCI has been recently extended towards non-disabled individuals with applications in gaming, entertainment, and 3D virtual environments.

BCIs designed for use in virtual environments provide several advantages to researchers. Use of interactive feedback from the task, increases protocol engagement and subject motivation, two factors which have been associated with improved BCI performance [2] along with reducing training times [3]. Virtual reality BCI systems have been implemented to prototype control of physical systems such as wheelchair and other robotic systems [4, 5], as well as provide test-bed platforms for further BCI development [6].

The P300 spelling matrix BCI first described by Farwell and Donchin [7] is considered one of the classic BCI systems. It relies on the elicitation of the P300 event-related potential (ERP) through an oddball paradigm of randomly intensified icon rows and columns. The P300 component of

the ERP is associated with a positive peak that develops approximately 300ms after a rare stimulus is intensified. By instructing participants to focus on a particular target, the intensification of that target will produce a stronger P300 than non-target intensifications. After online processing, classified results were used to drive a virtual alpha-numeric keyboard. P300-based BCI systems possess the advantages of rapid development, minimal training times and relatively high information transfer rates [8].

The use of P300 for spatial navigation has not been fully explored but has been described for virtual and physical control of wheelchair systems involving automated navigation have been reported in literature [9, 10]. Another study used a P300 system which featured position selection as a component of a virtual environment control system in which the subject's avatar was automatically moved to a specified virtual destination [11]. Additionally a study adapting a four-direction P300 cursor control system to a four door selection task has been reported [12]. In that study, each room in the virtual environment was identical, and additional icons next to targets were used to identify the desired action rather than information from a spatial task.

This paper documents the development and demonstration of a P300 based BCI system that allows guided free-form spatial navigation in complex virtual 3D environments. A new P300 matrix was developed that controls navigation from first person view in the virtual environment. The system was created through the integration of two freely available software packages: the BCI2000 framework [13] and the MazeSuite virtual environment platform [14-16].

### II. MATERIALS AND METHODS

#### A. Subjects

Ten (9 male, 1 female) healthy right-handed (Edinburg Handedness Inventory[17] LQ = 64±23.75) participants aged 19-23 (mean age=22.1) volunteered to participate in the experiment however one subject was discarded due to technical issues with recording equipment (N=9). Each individual gave written informed consent through documentation approved by the Drexel University IRB and answered demographic and survey questions related to the protocol. Participants were paid for their time, self-selected based on exclusion criteria concerning drug usage and prescription medications known to have psychiatric effects, and all self-reported no prior experience in BCI use or research.

#### B. EEG Setup

Data acquisition was completed using a Neuroscan

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Synamps2 40-channel EEG amplifier on a Windows XP computer running Neuroscan Acquire 4.5. EEG measurements were taken from 9 electrode sites (FCz, Cz, CP3, CPz, CP4, P3, Pz, P4, Oz) according to the international 10-20 system with A1 and A2 serving as reference and ground locations. Recordings were taken using a sampling frequency of 1 kHz with a software band pass filter between 0.5Hz and 60Hz and an additional notch filter at 60 Hz to remove electrical line noise. Measurements were recorded by Acquire and transferred to BCI2000 using the NeuroscanAccess module, and finally to a custom analysis module in Matlab for online processing.

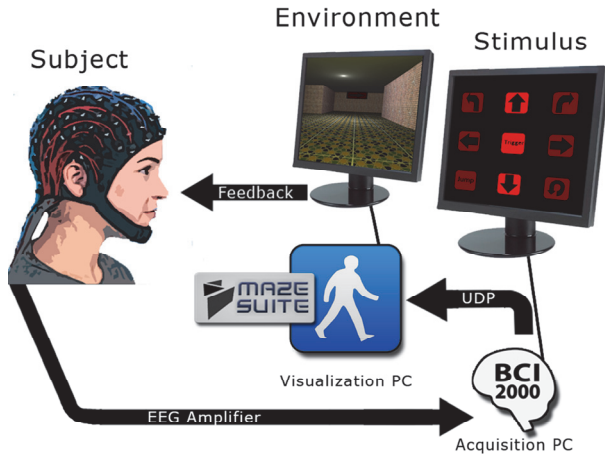


Fig. 1. Schematic diagram of experimental system: Acquired EEG data were analyzed by the acquisition PC. Stimulus timing and presentation was handled by the acquisition PC. Classifications based on extracted P300 components were forwarded as command signals to the MazeSuite PC where the virtual environment was updated.

### C. Experimental Setup

Subjects were seated at a comfortable distance in front of a two monitor display system with an independent computer controlling each monitor. BCI stimulus presentation was performed using a modified BCI2000 P3Speller application on the computer running the EEG acquisition software labeled Acquisition PC (See Fig.1). The navigational matrix was presented on the right-hand side monitor. Commands processed from the collected EEG signals were forwarded to the second computer, labeled Visualization PC in Fig.1 and rendered using the MazeSuite interactive virtual environment software with the environment presentation occurring on the left-hand side adjacent monitor. A dual computer setup was chosen to allow more flexibility with the online-processing and to prevent such processing from interfering with display of the environment. Communication between the two devices was handled through TCP/IP using a component of the MazeSuite API. Recordings took place in a faraday cage to minimize subject distraction from the task as well as shielding from electromagnetic interference in the EEG signal.

### D. BCI Protocol

BCI presentation was performed using the BCI P3Speller

application and follows the classic P300 spelling matrix paradigm [7]. The navigational matrix consisted of a 3x3 icon set with symbolic actions indicated by an image. Standard actions made available to the user included 90 degree turns, left/right strafe, jump, a 360 degree “lookaround” function, forward and backwards motion. Each column and row of the matrix was flashed randomly for 80ms for 10 sets with an interstimulus interval of 160ms, representing a total of 20 flashes per icon, and a total presentation time of 14.4 seconds. The ERP window for each epoch was assigned as 0-1000ms after stimulus onset. Subjects were asked to gaze at the target icon and count the number of times the target icon flashed. After each set of flashes, the recording was processed by Matlab using a step-wise linear discriminant algorithm (SWLDA), and the resulting classification was forwarded to MazeSuite for execution of the virtual movement command.

The subject was informed of the system’s activities by a series of dialogues which directed the user to attend either the matrix, or the virtual environment using instructions such as “Look at Matrix” given 2 seconds before initiation of the P300 stimulus and “Look at Maze” given just after the P300 stimulus period ended.

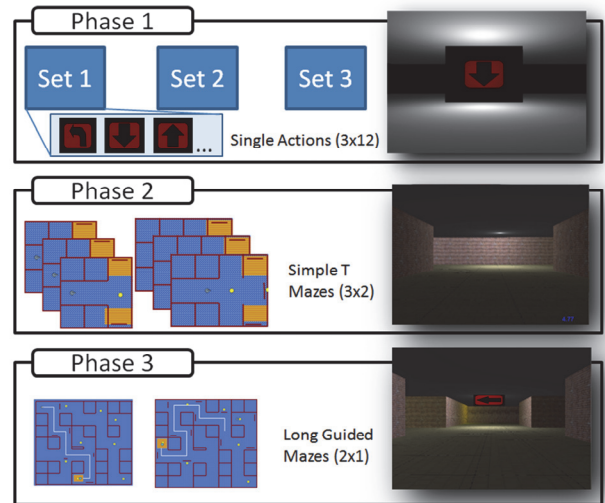


Fig. 2. Schematic representation of navigational task protocol: Phase 1 contained 3 sets of 12 “single-action” environments, each ordered randomly. Phase 2 contained 2 mazes with 3 repetitions each in a pseudorandom order. Phase 3 contained 2 long guided mazes presented sequentially. Top down representations were not shown to subjects.

### E. Task Protocol

The experimental procedure was divided into three phases, lasting a total of 90 minutes after consent and setup. Subjects were offered breaks between phases and they were naïve to the virtual environments used in the study.

The first phase served as a training segment with two goals in mind-- first, to familiarize the user with the P300 elicitation task as well as the functions of the navigational matrix, and second, to calibrate the system to the subject’s individual P300 response. Subjects were presented with a “single-action” environment in which the required action

was clearly indicated to the subject via presentation of the target icon. After examining the environment for a short period of time, the subject was asked to engage in the BCI task.

Recorded signals and target/non-target information were used for online training of the SWLDA classifier. After classification and execution of maze movement, the next “single action” environment was loaded. Three sets of 12 environments were completed with a short break between sets.

The second phase presented the user with several short “T-shaped” maze environments in order to test system accuracy and introduce the user to sequential command execution for navigation. Subjects were presented with two different short mazes labeled “T” and “Double-T”, three times each in a random order. Subjects were asked to navigate to a clearly marked exit. The exit location could be in one of four different corners such that subjects needed to search by navigating to different directions. After successfully reaching the end of the maze, the next environment was loaded.

The final phase consisted of two long guided mazes with the intention of measuring the user’s performance in a complete navigational task. Each maze contained a clearly marked path to the exit door and the next environment was loaded upon completion.

During the second and third phases, subjects were asked to record their intended actions using a number-pad matching the style of the navigational matrix in order to analyze BCI classification accuracy post-hoc. This input was not used to inform the online SWLDA classifier.

### III. RESULTS

#### A. Phase 1 Offline Performance

Results from the naïve classifier presented to the subject during training of the classifier are inherently error-prone, therefore Phase 1 accuracy and bitrate of each set was assessed using classifiers trained from the remaining two sets using step-wise linear regression for off-line cross-validation purposes. Mean classifier accuracy vs. number of stimuli sequences for the cross-validation is shown in Fig 3.

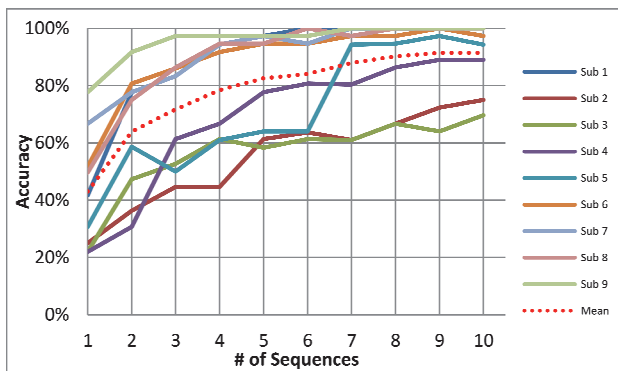


Fig. 3. Phase 1 offline cross-validation: Mean classifier accuracy vs. number of stimuli sequences.

After a total of 10 sequences the mean classifier accuracy was reported as 91.4% with standard deviation of 15.4%.

#### B. Online Performance

Bitrates per trial were calculated according to the equation described in [8].

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \frac{1-P}{N-1} \quad (1)$$

where N is the total number of available targets and P is the accuracy of the classification.

During online performance, classified actions were compared to recorded intended actions. Mean bitrates were calculated for each phase and for the overall accuracy for Phase 2 and Phase 3 which are listed in Table I and II. Bitrates in this study have been reported as ‘per trial’ due to a design choice to lengthen the inter-trial periods.

TABLE I  
PHASE 2 ACCURACY AND MEAN BITRATE

Trial	1	2	3	4	5	6	Mean	Bitrate
Subject	Accuracy							
1	75.0	100.0	100.0	100.0	100.0	100.0	95.8	2.80
2	62.5	75.0	83.3	80.0	60.0	100.0	75.0	1.61
3	71.4	100.0	66.7	100.0	100.0	66.7	84.0	2.06
4	80.0	100.0	75.0	100.0	75.0	100.0	86.4	2.19
5	80.0	66.7	80.0	60.0	66.7	55.6	66.7	1.25
6	100.0	100.0	100.0	100.0	100.0	100.0	100.0	3.17
7	100.0	100.0	100.0	100.0	100.0	75.0	95.8	2.80
8	100.0	100.0	100.0	100.0	100.0	100.0	100.0	3.17
9	83.3	100.0	100.0	100.0	100.0	100.0	96.2	2.82
Mean	83.6	93.5	89.4	93.3	89.1	88.6	88.9	2.33

Bitrate is reported per trial (14.4s/trial).

TABLE II  
PHASE 3 AND OVERALL ACCURACY AND MEAN BITRATE

Subject	Phase 3				Overall	
	Trial 1	Trial 2	Mean	Bitrate	Mean	Bitrate
1	89.5	100.0	94.7	2.71	95.2	2.75
2	80.0	51.6	62.7	1.10	67.8	1.30
3	70.8	50.0	60.0	1.00	68.0	1.31
4	71.4	63.3	66.7	1.25	72.6	1.50
5	76.9	72.0	73.7	1.55	70.3	1.40
6	100.0	94.4	97.0	2.88	98.2	2.99
7	100.0	90.5	94.4	2.69	95.0	2.73
8	94.7	76.2	85.0	2.11	90.6	2.44
9	100.0	100.0	100.0	3.17	98.2	2.99
Mean	87.0	77.6	81.6	1.93	84.0	2.06

Overall accuracy is recorded as the accuracy over all Phase 2 and 3 trials. Bitrate is reported per trial (14.4s/trial).

### IV. DISCUSSION

EEG-BCI systems have become increasingly accessible due to reductions in the cost of equipment, and the availability of specific software platforms such as the BCI2000 [13]. The P300 based control paradigm has been classically investigated for spelling tasks and more recently for additional control mechanisms. Use of the P300 based control paradigm for virtual environments is still not fully explored [9, 10] especially for spatial navigational control and problem solving (way-finding).

This study demonstrated a new P300 based BCI for spatial navigation control in virtual 3D environments that subjects used for searching exits and way-finding tasks.

These capabilities were tested using abbreviated “T shaped” labyrinths and guided way-finding tasks in longer more complex environments. Subjects achieved an average online accuracy of 84% using the proposed system. Online system performance from subjects included in the study is on par with other previously reported P300 interfaces [8, 18] where results between 80 and 95% for online accuracy are common and higher values for offline accuracy are often noted. It has been previously reported that BCI accuracy rates above 70% indicate lower threshold for system communication [8].

Virtual environments were designed and rendered using MazeSuite software which is a set of tools developed at Drexel University and provides researchers a platform for the rapid design, development and deployment of 3D virtual environments for use in controlled spatial and navigational studies [15]. We have already demonstrated an optical BCI with MazeSuite using Functional Near Infrared Spectroscopy [14]. Future work will include expanding the subject pool and providing this system to serve clinical populations such as ALS patients. The proposed system also opens the door for more complex BCI based navigational tasks for use in both research and multimedia/gaming applications. These applications could include acceptable performance in noisy environments and real world settings. MazeSuite development will continue to provide a testing ground for future BCI methods and applications.

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#### REFERENCES

- [1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland *et al.*, “Brain-computer interfaces for communication and control,” *Clin Neurophysiol*, vol. 113, no. 6, pp. 767-91, Jun, 2002.
- [2] R. Leeb, F. Lee, C. Keinrath *et al.*, “Brain-computer communication: motivation, aim, and impact of exploring a virtual apartment,” *IEEE Trans Neural Syst Rehabil Eng*, vol. 15, no. 4, pp. 473-82, Dec, 2007.
- [3] R. Scherer, F. Lee, A. Schlogl *et al.*, “Toward self-paced brain-computer communication: navigation through virtual worlds,” *IEEE Trans Biomed Eng*, vol. 55, no. 2 Pt 1, pp. 675-82, Feb, 2008.
- [4] Y. Arbel, R. Alqasemi, R. Dubey *et al.*, “Adapting the P300-brain computer interface (BCI) for the control of a wheelchair-mounted robotic arm system,” *Psychophysiology*, vol. 44, pp. S82-S83, 2007.
- [5] R. Leeb, D. Friedman, G. R. Muller-Putz *et al.*, “Self-paced (asynchronous) BCI control of a wheelchair in virtual environments: a case study with a tetraplegic,” *Comput Intell Neurosci*, pp. 79642, 2007.
- [6] J. Faller, G. Muller-Putz, D. Schmalstieg *et al.*, “An Application Framework for Controlling an Avatar in a Desktop-Based Virtual Environment via a Software SSVEP Brain-Computer Interface,” *Presence-Teleoperators and Virtual Environments*, vol. 19, no. 1, pp. 25-34, Feb, 2010.
- [7] L. A. Farwell, and E. Donchin, “Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials,” *Electroencephalogr Clin Neurophysiol*, vol. 70, no. 6, pp. 510-23, Dec, 1988.
- [8] E. W. Sellers, D. J. Krusienski, D. J. McFarland *et al.*, “A P300 event-related potential brain-computer interface (BCI): the effects of matrix size and inter stimulus interval on performance,” *Biol Psychol*, vol. 73, no. 3, pp. 242-52, Oct, 2006.
- [9] G. G. Gentiletti, J. G. Gebhart, R. C. Acevedo *et al.*, “Command of a simulated wheelchair on a virtual environment using a brain-computer interface,” *Irbm*, vol. 30, no. 5-6, pp. 218-225, Nov-Dec, 2009.
- [10] I. Iturrate, J. M. Antelis, A. Kubler *et al.*, “A Noninvasive Brain-Actuated Wheelchair Based on a P300 Neurophysiological Protocol and Automated Navigation,” *Ieee Transactions on Robotics*, vol. 25, no. 3, pp. 614-627, Jun, 2009.
- [11] G. Edlinger, C. Holzner, C. Groenegrass *et al.*, “Goal-Oriented Control with Brain-Computer Interface,” *Foundations of Augmented Cognition. Neuroergonomics and Operational Neuroscience*, Lecture Notes in Computer Science D. Schmorow, I. Estabrooke and M. Grootjen, eds., pp. 732-740: Springer Berlin / Heidelberg, 2009.
- [12] P. K. Piccione F., Tonin P., Vidale D., Furlan R., Cavinato M., Merico A. and Piron L., “Task and Stimulation Paradigm Effects in a P300 Brain Computer Interface Exploitable in a Virtual Environment: A Pilot Study,” *PsychNology Journal*, vol. 6, no. 1, pp. 99-108, 2008.
- [13] G. Schalk, D. J. McFarland, T. Hinterberger *et al.*, “BCI2000: a general-purpose brain-computer interface (BCI) system,” *Biomedical Engineering, IEEE Transactions on*, vol. 51, no. 6, pp. 1034-1043, 2004.
- [14] H. Ayaz, P. A. Shewokis, S. Bunce *et al.*, “An optical brain computer interface for environmental control,” *Conf Proc IEEE Eng Med Biol Soc*, vol. 2011, pp. 6327-30, 2011.
- [15] H. Ayaz, P. A. Shewokis, A. Curtin *et al.*, “Using MazeSuite and functional near infrared spectroscopy to study learning in spatial navigation,” *J Vis Exp*, no. 56, 2011.
- [16] H. Ayaz, S. L. Allen, S. M. Platek *et al.*, “Maze Suite 1.0: a complete set of tools to prepare, present, and analyze navigational and spatial cognitive neuroscience experiments,” *Behav Res Methods*, vol. 40, no. 1, pp. 353-9, Feb, 2008.
- [17] R. C. Oldfield, “The assessment and analysis of handedness: the Edinburgh inventory,” *Neuropsychologia*, vol. 9, no. 1, pp. 97-113, Mar, 1971.
- [18] J. N. Mak, Y. Arbel, J. W. Minett *et al.*, “Optimizing the P300-based brain-computer interface: current status, limitations and future directions,” *J Neural Eng*, vol. 8, no. 2, pp. 025003, Apr, 2011.