# Playing Checkers with Your Mind: An Interactive Multiplayer Hardware Game Platform for Brain-Computer Interfaces

Aadeel Akhtar, James J. S. Norton, Mahsa Kasraie, and Timothy Bretl

*Abstract*— In this paper we describe a multiplayer brain-computer interface (BCI) based on the classic game of checkers using steady-state visually evoked potentials (SSVEPs). Previous research in BCI gaming focuses mainly on the production of software-based games using a computer screen—few hardware-based BCI games using a physical board have been developed. Hardware-based games can present a unique set of challenges when compared to software-based games. Depending on where the user is sitting, some stimuli might be farther away from the player, at a steeper viewing angle, conflated with competing stimuli, or occluded by physical barriers. In our game, we light squares on a checkerboard with flickering LEDs to elicit SSVEP responses in the subjects. When a subject attends to a particular square, the resulting SSVEPs are classified and a robot arm moves the selected piece. In a set of pilot experiments we investigated the ability of two subjects to use the SSVEP-based hardware game platform, and assessed how interstimulus distance, interstimulus angle, distance between target stimulus and subject, number of competing stimuli, and visual occlusions of the stimuli influence classification accuracy.

## I. INTRODUCTION

Brain-computer interfaces (BCIs) allow users to control external devices based solely on changes in brain activity. Since BCIs do not rely on the motor system, they provide severely paralyzed or locked-in individuals with a means to communicate [1]. The majority of BCIs rely on the measurement and classification of event-related potentials—electrical activity generated given specific events in the environment around the user—using electroencephalography (EEG). One commonly studied event-related potentials is the steady-state visually evoked potential (SSVEP). SSVEPs are elicited when a user focuses his attention on a flickering visual stimulus appearing at a frequency between 1-100Hz [2]. This focus in attention causes an entrainment between the user's neural activity and the attended stimulus, which can be detected in the frequency domain.

Since SSVEPs are dependent on attention, it is possible for users to select a *target* stimulus from a set of simultaneously presented flickering stimuli. This property is used in SSVEP-based BCIs to determine user selections. There are several advantages to SSVEPs compared with other BCI paradigms. SSVEPs require little to no pre-run classifier training and have higher information transfer rates than BCIs based on

A. Akhtar is with the Neuroscience Program and Medical Scholars Program, J. Norton is with the Neuroscience Program, and T. Bretl is with the Department of Aerospace Engineering, University of Illinois at Urbana-Champaign, Urbana, IL, 61801, USA {aakhta3,jnorton4,tbretl}@illinois.edu. M. Kasraie was formerly with the Department of Aerospace Engineering, University of Illinois at Urbana-Champaign, and is now with Accenture Interactive mahsa.kasraie@gmail.com.
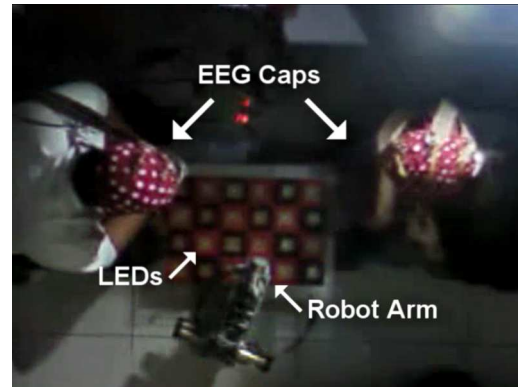
Fig. 1. Overhead view of the SSVEP checkers system with two subjects sitting on either side of the LED stimulus checkerboard. The robot arm is used to pick and place pieces.

the P300 (a neural response to infrequent stimuli) or motor imagery (imagined left/right movements) [3]. As a result, a wide range of SSVEP-based BCIs have been developed for a diverse set of applications, from controlling a rehabilitative arm [4], to driving a small car [5], [6], to playing games [7].

Considering the use of SSVEP-based BCIs for games, Lalor et al. [7] developed the first SSVEP-based game. This game, MindBalance, challenged a single-player to help a character cross a tight-rope. Periodically, the character would stumble, requiring the user to select targets using SSVEP. In 2007 Martinez et al. [8] developed Free Race, an optimized SSVEP game for navigating a car around a track. This game demonstrated the speed at which an SSVEP-based game could perform. In 2010 Mühl et al. [9] developed a hybrid BCI game, using both SSVEP and alpha neurofeedback as a part of the gaming experience. Recently, Maby et al. [10] explored how BCIs could increase the fun of classic games, demonstrated through an implementation of Connect Four.

Despite the proliferation of SSVEP-based games, they are predominantly implemented using software. This limits users to playing in front of monitors, which might not always be desirable. Through the use of wireless EEG hardware and LEDs, there is no reason that SSVEP-based games could not be developed for more traditional table-top settings. Hardware-based games present a unique set of challenges when compared with software-based games. Depending on where the user is sitting, some stimuli might be farther away from the player, at a steeper viewing angle, conflated with competing stimuli, or occluded by physical barriers. To determine whether these factors influence user performance, we developed a BCI version of the classic game of checkers.
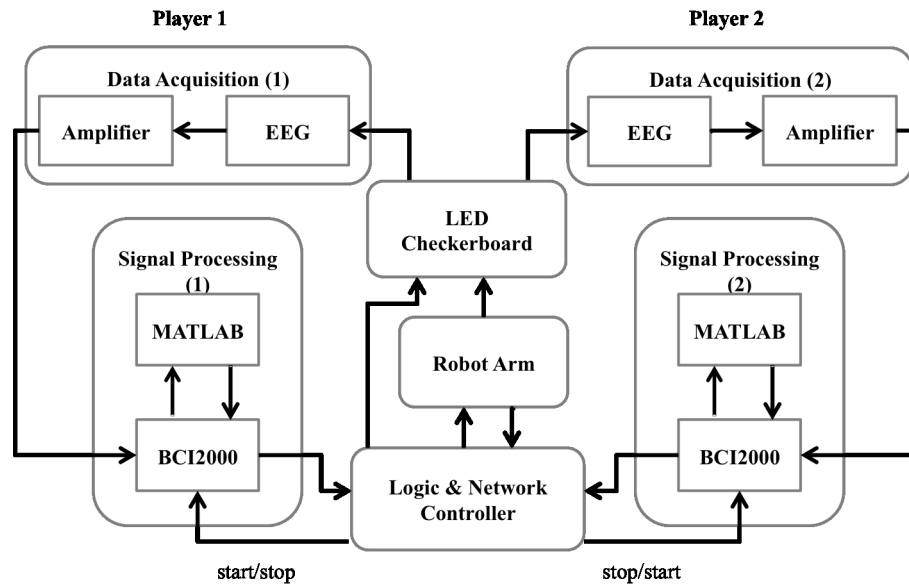
Fig. 2. A flowchart depicting the stimulus presentation, data acquisition, signal processing, classification, and end effector processes for two players.

Our game allows two players to compete using a single set of shared SSVEP stimuli. A robotic arm is used to move the pieces, allowing the entire game to be played using only EEG. In a set of pilot experiments we investigated the ability of two subjects to use the SSVEP-based hardware game platform, and assessed how interstimulus distance, interstimulus angle, distance between target stimulus and subject, number of competing stimuli, and visual occlusions of the stimuli influence classification accuracy.

## II. METHODS

### A. Subjects & Environment

Data were collected from 2 healthy participants (1 male and 1 female) both in their 20s. The subjects were seated in a room with dim lighting about 75-85cm above the stimuli with viewing angles of 40-60° below the horizon (Fig. 1).

### B. Setup

A flowchart describing the overall system design for two players is shown in Fig. 2. A 6x4 checkerboard with each square housing a single white LED was used to produce the stimuli (Fig. 3). The Plexiglas layer on top of the LEDs was divided into 24 squares, with each square having an outer border of 9cm and an inner border of 5.5cm, leaving a 5.5cm$^2$ area for the subject to observe the stimulus. Eight Plexiglas game pieces were developed, each was a bottomless cube of 5.5cm$^3$ with edges painted red or black. The pieces were clear in order to minimize the obstruction of the stimuli when they were placed on the game board.

Since SSVEPs generated by stimuli in the upper alpha wave region (10-13Hz) provide the greatest signal-to-noise ratio (SNR) [5], [6], [11] our game utilized white LEDs flickering at 10, 11, 12, and 13Hz. A duty-cycle of 40% was chosen, because it has been previously demonstrated to maximize SNR [12]. Stimuli indicated the moves available



(a)
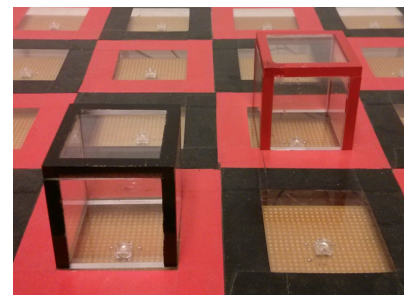


(b)

Fig. 3. The LED checkerboard and robot arm (a) and the pieces (b).

to a player on a given turn, with between two to four LEDs lit at a time. When only one move is available, the system automatically makes the move without user input. EEG was measured from electrodes placed at seven recording sites (*PO*3, *PO*4, *PO*7, *PO*8, *O*1, *O*2, *Oz*) over the visual cortex according to the 10-5 international system. Electrodes were referenced to the vertex and grounded using an ear-clip. The

signals were amplified by a James Long Biosignal Amplifier before being recorded and analyzed using BCI2000 [13]. All data were acquired in blocks of 8 samples at a rate of 256Hz.

## C. Feature Extraction and Classification

Feature extraction and classification was done using BCI2000's MATLAB Filter. To reduce false positives during the game, the available stimuli were lit for two seconds before signal processing and classification began. Spatial filtering was performed by taking 4 Laplacian derivatives as outlined in [5], [6], shown to maximize the SSVEP signal with $Oz$ as the location of interest.

A 4096-pt FFT was taken over each Laplacian. Since it has been shown that EEG can discriminate SSVEP up to 0.2Hz [11], a ratio of peak power to average noise level was calculated by finding the peak power over 6 bins centered around the first harmonic (i.e. stimulus frequency $\pm$ 0.18Hz) of the target frequencies (10, 11, 12 and 13Hz) then dividing the peak value by the average power of the remaining signal between 9.8Hz to 19.8Hz. The range 9.8Hz to 19.8Hz was chosen to exclude extraneous power resulting from lower-band alpha activity [11] and higher-order harmonics [2]. To classify the signal, the mean of all four ratios must pass a threshold value of 5, determined a priori. In other words, on average, the signal peaks must be 5 times greater than the noise in order to be classified. If none of the ratios for the four frequencies reach the threshold within 20 seconds, the signal processing and classification was restarted.

Following classification, the target selection was sent to the logic and network controlling program. This program coordinated the checkers logic, whose turn it was, which stimuli were lit, and the movement of the robot arm (Rhino XR-3, Mark III Controller). For each move, we recorded the classification and the spatial configuration of the stimuli.

## III. RESULTS

The performance results for the two subjects are shown in Table I. The subjects completed four games with a varying number of selections per game and per person. Overall, Subject 2 (92.2% accuracy) performed better than Subject 1 (72.9% accuracy). A total of 98 selections were made by both players, with 17 errors total.

Among the 17 errors, the distances between the target and misclassified stimuli, as well as the angle between them is shown in Fig. 4. The angles range from 0-360°, with 0° meaning that the misclassified stimulus was located in the same row to the right of the target stimulus. In 9 of the 17 errors, the misclassified stimulus was located closer to the subject than the target stimulus. On average the distance between the subject and the target stimulus was $95.2 \pm 8.0$cm, ranging from 85.2-114.6cm. The average distance between the subject and the misclassified stimulus was $93.9 \pm 8.2$cm, ranging from 85.4-108.0cm. There were no general trends in any of these cases.

Of the 98 selections made, 73 of them involved selecting a square with a piece placed above it, and the other 25 involved selecting an empty square. An analysis of the classification

PERFORMANCE RESULTS FOR THE TWO SUBJECTS OVER ALL GAMES PLAYED. ERRORS ARE DEFINED AS WHEN THE CLASSIFIER DID NOT CORRECTLY SELECT THE TARGET STIMULUS.

| Subject | Number of Selections | Number of Errors | Accuracy |
|---------|---------------------|------------------|----------|
| Subject 1 | 47 | 13 | 72.3% |
| Subject 2 | 51 | 4 | 92.2% |
| Total | 98 | 17 | 82.7% |

errors revealed that in every error that occurred, the stimuli had pieces placed over them (i.e. the subject was selecting which piece to pick up). Furthermore, the majority of these errors were made when there were more than two stimuli on at the same time. Out of the 57 two-stimulus choices, only 6 were errors—compared to 11 out of the 41 choices with more than two stimuli.
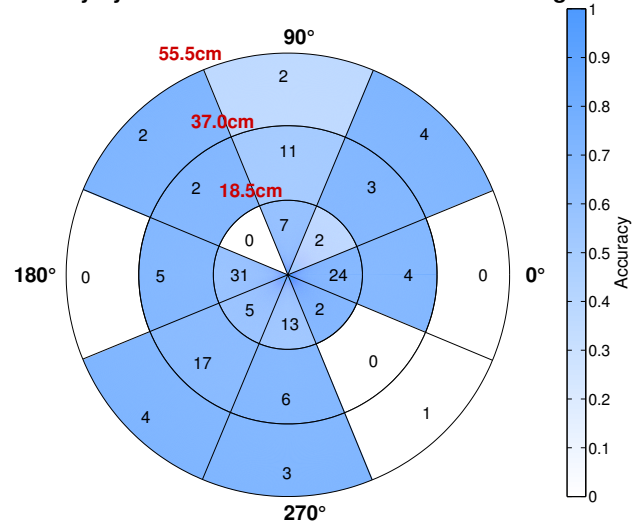


Fig. 4. Donut plot showing the classification accuracy for combinations of the distance and angle between the target and competing stimuli. Each users' selections were divided into 3 interstimulus distance ranges, increasing along the radius of the donut, and 8 interstimulus angles, increasing around the circumference of the donut. An interstimulus angle of 0° means that the misclassified stimulus was located in the same row to the right of the target stimulus. The numbers within each of the 24 regions represents the total number of selections for that particular combination of interstimulus distance and angle, while the color represents the classification accuracy.

## IV. DISCUSSION

The subjects were successfully able to select squares on the board and were able to play through full games. Furthermore, the users were able to achieve relatively high accuracy for an SSVEP-based BCI [5], [6]. However, one of the subjects did perform better than the other. This could be attributed to the fact that Subject 2 had more experience using SSVEP than Subject 1. Also, studies suggest that females (Subject 2) may be better at generating SSVEPs than males (Subject 1) [14]. Regardless, Subject 1's 72.3% accuracy rate suggests that even users with little to no experience with SSVEP can still achieve decent performance.

Interstimulus distances and angles, as well as the distance between the subject and the stimuli could also influence the signal classification. Fig. 4 does not show any consistent trend. However, there were not enough error cases for each of the configurations to truly determine whether there is a significant relationship between classification accuracy and interstimulus distance or interstimulus angle. In regard to the distance between the user and the target stimulus, even though closer LEDs appear brighter in the visual field, Valbuena et al. found that there was no difference in classification between LEDs placed either 50 or 70cm from the subject [4]. While our participants were seated slightly more than 70cm from the stimuli, the data does not show a trend that favors any particular distance to the target stimuli.

The decrease in classification performance that occurred when there were more than two stimuli on at the same time is supported by literature. Stimuli that resonate at frequencies in the upper alpha wave region compete for neural resources in the brain, which results in less neurons firing at the same frequency as the target stimulus, and a lower peak SSVEP power [15]. Increasing the number of competing stimuli in the upper alpha region further decreases the peak SSVEP power for the target stimulus in that region.

The fact that all of the errors occurred when the pieces were placed over the square is an important point. Even though subjects could see the LED through the piece because it was made out of Plexiglas, the reflection of the light off of the sides of the cube could have interfered with perceiving the stimulus at a time-locked and phase-locked frequency. This reflection could have also reduced the amount of light to reach the eye, thereby reducing the power of the resulting SSVEP. High amounts of environmental light may also be a negative contributor to the accuracy of SSVEP. In preliminary runs under bright environmental lighting settings, signals appeared noisier. The noise generated by environmental light would make it harder to discriminate signal peaks from the background noise. Additionally, it reduces the apparent brightness of the LEDs. In order to increase the accuracy of a system like the one presented, techniques such as blind source separation [16] and minimum energy [17] could be used to separate the noise from the SSVEP peak frequencies.

## V. Conclusions and Future Work

We have developed a multiplayer interactive hardware game platform for SSVEP-based BCIs. We detailed the implementation of the system from its LED inputs, to the data acquisition from the subject, to the signal analysis and classification, to controlling the robot, and then finally to the next player's turn. Additionally, we discussed the influence of interstimulus distance and angle, distance of the target stimuli to the subject, the number of competing stimuli, and visual occlusion of the stimuli. Future work will involve a more comprehensive study with larger sample sizes to determine whether these factors significantly influence classification. Finally, our hardware-based approach is not limited to gaming. By adding LEDs, SSVEP-based interaction could be enabled in a multitude of existing hardware systems.

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