Non-invasive Brain-machine Interface for MindPong Game using Electroencephalogram and Reservoir Computing Decoder*

Hoon-Hee Kim

I. Introduction

In the field of multimedia, various electroencephalogram (EEG) studies have been reported in the context of brain-machine interface research. Recently, Neuralink has demonstrated a prototype wherein they invasively measured the brainwaves of a primate and showed that it was possible to control the bar in the Pong Game merely by thought. However, this method, which involves the surgical installation of electrodes inside the skull for measuring brainwaves, poses difficulties for application to the people. Therefore, in this study, we designed a non-invasive EEG-based brain-machine interface and applied it to the Pong Game. In particular, we demonstrated that it is possible to decode the intention of manipulation directly, not through motor imagery, by measuring signals solely from the prefrontal cortex, unlike traditional brainwave decoders that use sensory-motor signals.

II. Methods

In this study, we measured EEG signals using the OpenBCI equipment. While OpenBCI provides up to 16 electrode channels, we only utilized the F7, F3, Fp1, Fp2, F4, and F8 channels for measuring prefrontal cortex brainwaves, corresponding to user intention signals. The sampling rate of the EEG measurement equipment was fixed at 125Hz. We collected EEG data from a total of 10 participants (20s, BMI inexperienced, healthy individuals), measuring 30 minutes per participant over 16 days, for a total of 480 minutes per participant, to train the decoder model. The OpenBCI used in this study measured data at a sampling rate of 125Hz, with a buffer of 0.5 seconds, resulting in time series data of lengths 62-63 per buffer.

EEG data preprocessing used six buffers of time series data, each with a window time of 3 seconds, and the window was shifted by 0.5-second bins. The preprocessing involved the application of a high-pass filter that passed signals of 1Hz or higher and a low-pass filter that passed signals of 60Hz or lower. A 60Hz notch filter was then applied to remove line noise. Subsequently, to extract features from the EEG data, we applied band-pass filters that passed the 0.5-4Hz, 4-8Hz, 8-12Hz, 12-30Hz, and 30-45Hz ranges, extracting four features corresponding to delta, theta, alpha, and beta waves.

The machine learning model used for decoding the brainwaves was a linear regression model, chosen for its relatively fast execution speed which enables real-time data processing. We preprocessed the EEG data measured when the participant thought about commanding the game bar to move up or down, extracted brainwave features, and used the concurrently recorded class data to train the machine learning model to decode the user's brainwaves.

For effective brainwave decoding, we designed a EEG decoder following the Reservoir Computing Paradigm. In this decoder, the readout was designed to follow a Gaussian distribution, representing the selectivity of the decoding direction with dynamics similar to simple cells.

III. Results

For each of the 10 subjects, we constructed separate models for decoding EEG and carried out a total of six games, each lasting 3 minutes. This was done under various conditions, combining difficulty levels of 0.1, 0.5, and 0.9 (with 0 indicating a high directional automatic guidance ratio) and bar movement speeds of 5 and 6. We repeated this process 10 times to measure the results. During gameplay, we recorded instances of the AI blocking the ball (AI_Hit), the user blocking the ball (User_Hit), the AI missing the ball (AI_Miss), and the user missing the ball (User_Miss) for performance evaluation.

Tables 1 and 2 show the results of AI and user Hits and Misses. In the case of AI, the variance was relatively low at 3.82 and 3.91, showing similar performance regardless of the game's difficulty or speed. In terms of misses, the AI averaged 6.5 misses, while human users averaged 3.48, indicating that users missed fewer balls.

Table 3 provides results based on difficulty. It demonstrated differences between the AI and users across all difficulty levels. As difficulty increased, the average number of Misses by the user also increased, reducing the average difference in the number of missed balls between the user and the AI.

Table 4 reveals results from varying the bar's movement speed (speed) at different difficulty levels. When the bar's movement speed was increased from 5 to 6, both human and AI Hits showed an increasing trend. At a difficulty of 0.1, AI Hits increased from 9.9 to 12.6, while user Hits rose from 10 to 13.8. However, while AI Misses also increased from 6.6 to 7.3, user Misses decreased from 3.6 to 2.7. This trend was consistent across different difficulty levels. Moreover, when the bar's movement speed was 6, both the AI and user Misses tended to increase as the difficulty increased. At a bar's movement speed of 5, the trend of AI and user Misses differed. As the difficulty level increased, user Misses increased, but AI Misses decreased. Solely considering misses, users missed

* This study was supported by Startup Growth Technology Development Project (No.1425174568), the National Police Agency and the Ministry of Science, ICT & Future Planning (Grant no: 1711174175) and the Pukyong National University Research Fund in 2022(202212510001).

F. A. Author is with Pukyong National University, Republic of Korea (corresponding author to provide phone: +82-51-629-6244; e-mail: h2kim@pknu.ac.kr).

fewer balls at difficulty levels 0.1 and 0.5, but missed more balls at a difficulty level of 0.9.

IV. Discussion

This study implemented a multimedia application system that enables a game of MindPong using a brain-machine interface (BMI) based on EEG. Notably, we used EEG applicable even to the general public and used only electrode channels corresponding to the prefrontal cortex, enhancing usability. The artificial intelligence model for decoding EEG in the BMI used a linear regression model capable of real-time processing. Consequently, the proposed BMI obtained equal or higher scores in battles against an AI that moved on the optimal path controlled solely by brainwaves. Thus, this study not only suggests the feasibility of developing multimedia game interfaces using EEG but also demonstrates that the results of this research can be applied to various multimedia interfaces.

TABLE I. Results of AI vs. User Hit

	AI_Hit	User_Hit
Mean	11.2	12.18
Variance	3.82	9.41

TABLE II. Results of AI vs. User Miss

	AI_Miss	User_Miss
Mean	6.5	3.48
Variance	3.92	3.98

TABLE III. Results of AI vs User (Difficulty)

Difficulty = 0.1	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	11.25	11.9	6.95	3.15
Variance	3.78	11.25	4.89	4.45
Difficulty = 0.5	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	10.7	12.05	6.85	4.6
Variance	3.06	10.16	2.45	21.73
Difficulty = 0.9	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	11.65	12.55	6.5	6.15
Variance	4.56	7.84	8.68	13.08

TABLE IV. Results of AI vs. User Hit

Difficulty = 0.1 **Speed = 5**	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	9.9	10	6.6	3.6
Variance	2.32	1.78	5.82	5.16
Difficulty = 0.1 **Speed = 6**	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	12.6	13.8	7.3	2.7
Variance	1.60	13.96	4.23	3.79
Difficulty = 0.5 **Speed = 5**	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	9.5	9.9	6.2	5.5
Variance	1.17	3.88	2.18	21.39
Difficulty = 0.5 **Speed = 6**	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	11.9	14.2	7.5	3.7
Variance	2.10	7.29	2.06	22.68
Difficulty = 0.9 **Speed = 5**	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	10.3	10.5	5.4	6.8
Variance	2.46	1.83	6.27	8.40
Difficulty = 0.9 **Speed = 6**	AI_Hit	User_Hit	AI_Miss	User_Miss
Mean	13	14.6	7.6	5.5
Variance	3.11	5.38	9.38	18.28