An Online Human-Agent Interaction System: A Brain-controlled Agent Playing Games in Unity

Demonstration Track

Zehong Cao*
University of Tasmania, Australia
zehong.cao@utas.edu.au

Jie Yun*
University of Tasmania, Australia
jie.yun@utas.edu.au

ABSTRACT

Human-agent interactions present people guide an object or agent to act as human intentions. This demonstration work develops an online human-agent interaction system, particularly targeting the brain-computer interface (BCI), which uses real-time brain cortex signals: electroencephalogram (EEG) to control the agent in Unity3D game platform. The developed system also provides the online visualisation of EEG signals, including pre-processed temporal data and power spectral in three frequency bands (theta, alpha, and beta). To build this systematic work, we firstly collect wireless EEG signals via the Bluetooth transmission from a commercially available 14-channel brainware headset (Emotiv). EEG signals are then pre-processed and fed into a trained deep learning model to predict the human intentions, which will be sent to Unity3D platform to control an agent's movements in game playing, such as a karting game scenario. The online testing results show the feasibility of our systematic work that will benefit for human-agent interaction community. **The demonstration video can be viewed at the following link: https://youtu.be/9AWKHeatc6I**

KEYWORDS

Human-agent Interaction; Brain-computer Interface; Unity Game

ACM Reference Format:
Zehong Cao and Jie Yun. 2021. An Online Human-Agent Interaction System: A Brain-controlled Agent Playing Games in Unity: Demonstration Track. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), Online, May 3–7, 2021*, IFAAMAS, 3 pages.

1 INTRODUCTION

Human-agent interaction (HAI) investigates interaction design approaches across conventional interactive systems, including physical robots, virtual agents, and human-computer communication [6]. Within these scopes, brain-computer interface (BCI) as shown in Fig. 1, serves as a linkage between human intentions and machine controls that allows users to interact with the computer-based commands transmitted directly from the human brain electroencephalogram (EEG) signals to the inputs of the computer [4].

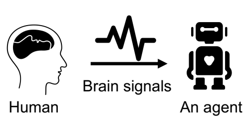

Figure 1: Brain-computer interface

Although the recent studies investigated BCI for HAI purposes, such as the driving fatigue assessment [3], most of them are only focused on off-line data processing and feature extractions or used a simple scenario that cannot integrate a flexible computer software platform to allow designing various agents or multiple visual objects. To complement these weaknesses, it is worth considering the EEG-based BCI headsets that are inexpensive, portable, and easy to set up, and develop an instant connection with a virtual agent. Also, it is vital to design online manipulations from the human brain to an agent. For example, a game player's brainwaves can be real-time recorded, analysed, visualised, and converted into commands to replace manual inputs for the agent controls. Furthermore, there is currently no open-source systemic work from our literature survey that links from online EEG recording, visualisation, and processing with a deep learning core to a flexible agent design platform, such as Unity3D for games. Thus, this study **aims** to develop an online human-agent interaction system: a brain-controlled agent playing games in Unity, **focusing on 1)** real-time brain signals recordings and visualisations from an EEG headset; **2)** human brainwaves to control an agent; **3)** create an agent playing game in Unity.

The **contributions** of our systemic work are: **1)** The developed system is the first open-source system that integrates online EEG recording, processing, visualisation with deep learning architecture and sends brain-controlled commands to a flexible agent design platform: Unity3D; **2)** Our system provides online visualisation of EEG signals, including pre-processed temporal data and power spectral in three frequency bands (theta, alpha, and beta), adding interpretability on the human brain activities in game playing; **3)** Our work will have some potential impacts, such as freeing the agent in games from the need for peripheral input devices and making controls available to people with mobility impairment.

2 THE SYSTEM ARCHITECTURES

2.1 Hardware

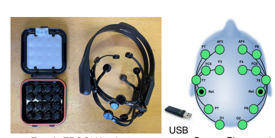

Figure 2: The hardware of the system architecture

*Equal Contribution.

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, Online.

As shown in Fig. 2, our proposed system architecture's hardware is the Emotiv EPOC+ headset kit [7], which includes a 14-channel neuroheadset to sense the whole brain, saline-based wet sensors to record EEG signals, and a USB dongle to wireless transmit the EEG signals to the computer. Before recording EEG signals, it is also required to check a good contact 100% (showed as the green colour) for 14 standard electrodes and reference sensors.

2.2 Software

In this systematic work, our proposed system architecture software is based on motor imagery (MI) data and Python development, as shown in Fig. 3. The source code is released at GitHub repository https://github.com/nomatterhoe/Online-EEG-HAI.

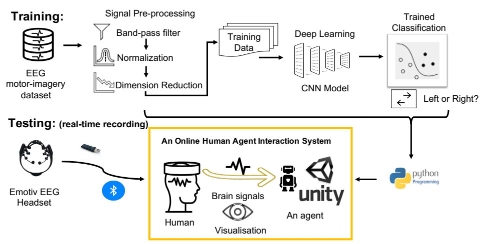

Figure 3: The software of the system architecture

2.2.1 *Motor imagery.*

A popular approach to achieve this comes from EEG-based MI prediction to control an agent using human intentions. MI is considered a dynamic state during which the human mentally simulates or feels to perform a physical action. This study used a benchmark EEG MI dataset (Graz-2a) [1] to build the pre-trained classification model.

2.2.2 *Python development.*

As shown in Fig. 3, firstly, we developed the EEG pre-processing module aiming to improve signal-to-noise ratio and minimise the artifacts, which includes the 1-30 Hz band-pass filter, Z-score normalisation, and dimension reduction using principal component analysis. Once the EEG signals are pre-processed, we identify the events of human moving intentions per second within the EEG signals, which can slice the EEG signals to create epochs for generating the training samples.

With the superior performance of Convolutional Neural Networks (CNN) in MI-EEG classification by learning human intention patterns [5], we implemented a 3-layer CNN to understand EEG features and predict/classify the human moving intentions (e.g., left or right moving direction), which includes a 3-layer max pooling to reduce dimensionality, and a fully-connected layer for final classification, along with dropout and batch normalisation to minimise the risk of overfitting. Finally, we created a visualisation interface to demonstrate the real-time pre-processed temporal EEG data and spectral EEG power representing three frequency bands (theta, alpha, and beta).

2.2.3 *Unity3D game engine.*

Unity is an open-source developer-oriented game engine platform, which includes several complex components useful to game developers and allows creating three-dimensional objects and agents for console games in Unity3D [2]. In this systemic work, Unity3D supports the C# programming language, and we build a Python API as above sending the classification outputs to the unity environment for developing high-performance brain-controlled games and applications.

3 EXPERIMENTS AND RESULTS

3.1 Training performance

To build the pre-trained prediction model to classify the human moving intentions, we use the existing benchmark MI dataset [1] to build a CNN classification model, and split the training and validation samples to get an intuition if the model can achieve the high classification accuracy. As shown in Fig.4, within 40 epochs, we can already settle on some hyperparameters that provide adequate performance.

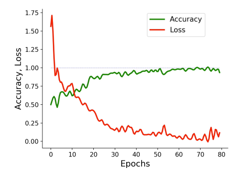

Figure 4: The training performance

3.2 The testing setup and performance

As shown in Fig. 5-A, we took some photos for the testing environment setup, including the hardware and software setup. We also attached some snapshots for real-time brainwave visualisation interface and the testing scenario - Unity karting game. As shown in Fig. 5-B, the karting game requires the agent to complete 3 checkpoints within 60s to win. The agent receive 5s reward for passing each checkpoint. The human controls the movement of the agent player using brain signals which are fed into a pre-trained prediction model and produce direction commands, moving left or right. In our testing case, the brain-controlled agent took 25 seconds to reach the goal (with 15s rewards) and won the karting game.

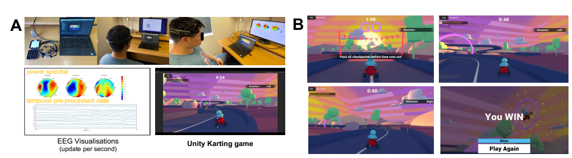

Figure 5: The testing setup (A) and karting game scenerio (B)

4 CONCLUSION

In conclusion, our systematic work is: **1)** easy to set up: the operation only requires a computer/laptop and a commercially available Emotiv EPOC+ EEG headset; **2)** scalable: it is easily applied to play various agent-based games on the Unity platform; **3)** novel: the first open-source integration of online recording, processing, visualising and learning architecture to handle EEG data and send brain-controlled commands to the Unity platform; **4)** interactive: it enables interactive gaming experience by allowing human players to interact with the agent in Unity games using brainwaves.

REFERENCES

[1] C Brunner, R Leeb, GR Muller-Putz, A Schlogl, and BCI Competition. 2008. Graz data set A. *Institute for Knowledge Discovery, and Institute for HumanComputer Interfaces Graz University of Technology, Austria* (2008).

[2] Ismail Buyuksalih, Serdar Bayburt, Gurcan Buyuksalih, AP Baskaraca, Hairi Karim, and Alias Abdul Rahman. 2017. 3D Modelling and Visualization Based on the Unity Game Engine–Advantages and Challenges. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 4 (2017), 161.

[3] Zehong Cao, Chun-Hsiang Chuang, Jung-Kai King, and Chin-Teng Lin. 2019. Multi-channel EEG recordings during a sustained-attention driving task. *Scientific data* 6, 1 (2019), 1–8.

[4] Xiaotong Gu, Zehong Cao, Alireza Jolfaei, Peng Xu, Dongrui Wu, Tzyy-Ping Jung, and Chin-Teng Lin. 2021. EEG-based Brain-Computer Interfaces (BCIs): A Survey of Recent Studies on Signal Sensing Technologies and Computational Intelligence Approaches and their Applications. *IEEE/ACM Transactions on Computational Biology and Bioinformatics* (2021).

[5] Vernon J Lawhern, Amelia J Solon, Nicholas R Waytowich, Stephen M Gordon, Chou P Hung, and Brent J Lance. 2018. EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces. *Journal of neural engineering* 15, 5 (2018), 056013.

[6] Avi Rosenfeld and Ariella Richardson. 2020. Why, Who, What, When and How about Explainability in Human-Agent Systems. In *Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems*. 2161–2164.

[7] Nikolas Williams, Genevieve M McArthur, and Nicholas A Badcock. 2020. 10 Years of EPOC: A scoping review of Emotiv's portable EEG device. *BioRxiv* (2020).