Data-driven Recommendation in Brain-Metaverse Interaction

Zihui Qin, Yilin Cao, Jeongyeong Park, Qianru Liu, Zhuohui Xu, Nanlin Jin, Hai-Ning Liang
School of Advanced Technology
Xi'an Jiaotong-Liverpool University
Suzhou, China
{zihui.qin21, yilin.cao20, J.Park2002, Qianru.Liu22, Zhuohui.Xu22}@student.xjtlu.edu.cn
and
{Nanlin.Jin, HaiNing.Liang}@xjtlu.edu.cn

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***Abstract*—Metaverse offers exciting new ways to experience digital worlds. However, there is limited work to understand and measure such experiences, lacking studies on the real-time interaction between people and metaverse-based virtual worlds, especially using biometrics. This work represents one of the first to investigate this opportunity, focusing on leveraging users' brain signals. We developed a prototype for Brain-Metaverse Interaction (BMI). This paper presents two contributions: (1) real-time interaction enabled by an IoT system. It integrates a virtual reality (VR) headset with brain signals and a multi-communication setup, which enables users to choose the most convenient communication tools from WiFi, Bluetooth, and a cable link; and (2) unlike most existing research and commercial applications to help people relax, our work recommends VR content appropriate to the users' current mental states. This work provides interesting insights into future research of BMI, for example, providing VR content that is adaptive and evolving based on users' mental state and relaxation level.**

***Index Terms*—Metaverse, Brain signal, Data mining, Internet of things**

I. Introduction

In the past decade, Virtual Reality (VR) offers a highly interactive experience, providing users with a strong sense of embodiment and immersion, and a rich way of providing feedback to users. On the other hand, unlike VR, Electroencephalography (EEG) devices lies in their ability to detect users' actual brain states and represent them visually. Leveraging these two technologies, our work aims to develop a system that integrates VR, EEG devices, and other devices via an Internet of Things (IoT) framework to evaluate and provide feedback (e.g., content adjustment) according to users' mental state.

This paper introduces an AI-enabled IoT system that is based on Brain-Metaverse Interaction (BMI), as depicted in Figure 1. The BMI system enables real-time interaction between the VR application and brain signals. Using an EEG headset, the system directly captures users' mental state in response to VR scenes. This unique tool facilitates personalised recommendations and enhances users' immersion in the virtual world.

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II. Related work

A. Human-machine interaction and user experience

There has been research into creating different experiences based on the user's mental health. Nayak et al. [1] have proposed a non-contact framework to classify affective states and hope to apply it as an aid for psychologists. Zhang [2] designed a college mental health guidance model based on data collection and fuzzy information extraction and verified its effectiveness. These studies focus on human psychological states and have helped frame our research. Sokoowska reviews how virtual reality can benefit brain health [3].

In addition, AI-based systems have recently become useful in creating customisable experiences. Gedeon [4] has proposed a concept called responsive AI, which combines AI and people's reactions as input and output components. This work used human-device interaction techniques to present human information and explore mental states. Sharma et al. [5] worked on the AI-enabled system to implement mouseless gesture control as an optimisation for user interactions. Similarly, Abbiss et al. [6] compared the advantages and disadvantages of mobile-based interactions and more traditional settings to give us a more comprehensive understanding of further possibilities that can integrate richer experiences.

B. Internet of things

Our research requires connecting VR devices, EEG devices, and computers through the Internet of Things. To achieve this, we found some relevant previous research. Dave et al. [7] proposed a new data solution called the MQTT-CoAP Interconnector (MCI) to enable interoperability between different devices, while Elewah et al. [8] investigated designs that enable IoT through platform access to independent cloud nodes. Instead of such long-distance connections, Ferreira et al. [9] studied a narrowband-IoT (NB-IoT) approach that consumes less power and works better in small areas. Furthermore, Uddin [10] discusses the possibility of introducing machine learning into IoT.

There is also some precedent for connecting VR devices to an IoT setup. Similarly to remote access to the cloud nodes

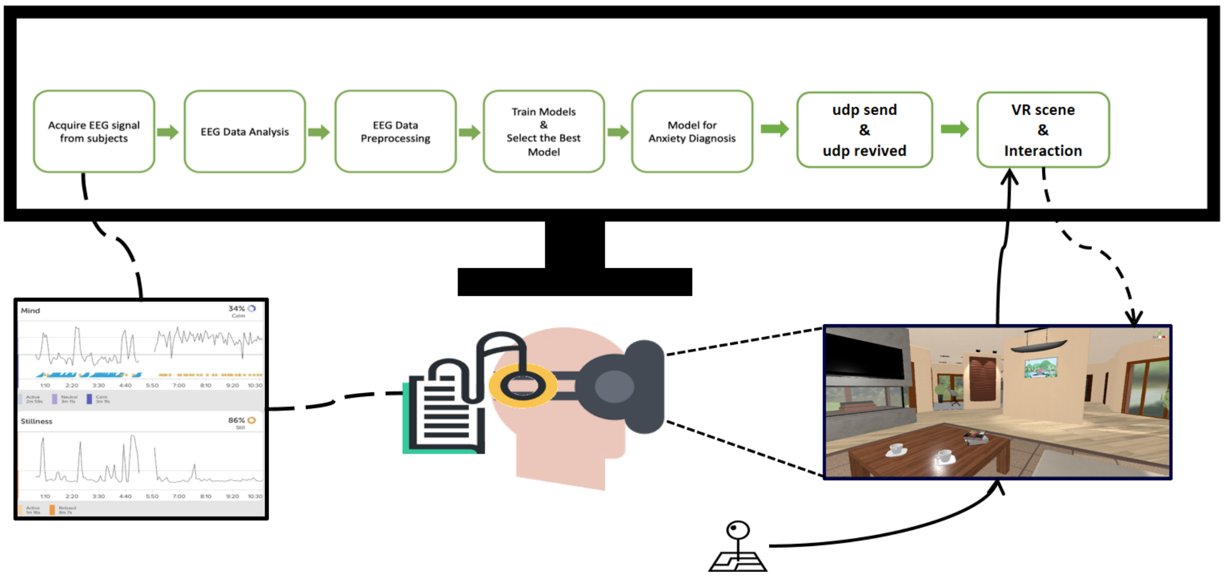


Fig. 1: The overall design of the BMI setup with the system's main components: connected hardware devices, brain signal acquisition, signal processing and analysis, and a view of the virtual world.

mentioned above, Simiscuka et al. [11] investigated cloud-enabled synchronisation of IoT and VR. Abbas et al. [12] proposed an IoT design that could support cross-platform connectivity to VR. In addition to related work on connectivity, some studies focus on optimisation and applications. Owais and Yaacoub [13] investigated the parallel use of VR and IoT traffic in remote areas based on the needs of mobile healthcare applications. On a more specific note, Elwageeh and Karoui [14] integrated IoT and VR to evaluate lighting designs and test artificial lighting preferences.

C. Brain signal and analysis

Brain signals often refer to data collected by Electroencephalography (EEG) devices that capture brain activities. Small sensors detect electrical data. EEG is one of the non-invasive biosignals [15]. EEG activity is measured in the unit of microvolts (mV). A rich body of research has been done on biosignal analysis. Take anxiety as an example, and we can find recent work showing that a variety of machine learning algorithms were used to analyse it, including clustering, feature selection, classification, and deep learning (CNN, LSTM) [15] [16].

The EEG signal is in the format of time series. Therefore, time series analysis methods, such as autoregressive moving average (ARMA) models and multivariate analysis, can be used. Furthermore, feature construction and feature calibration can be used for time series in the time domain [17]. Moreover, the frequency domain of EEG signal has also been well studied [18]. The frequencies of brain waves and their characteristics to human activities have been widely recognised, as well as mental states [19].

D. Recommendation systems in literature

Recommendation systems are often associated with machine learning [20]. They are usually built based on users' activities, such as search history, purchase records, and/or demographic characteristics, to provide personalised recommendations for services and/or products [21]. Such recommendations are expected to have a higher probability of fitting users' needs or interests. There are two typical stages: first, to understand the users from data and using data mining, and then to search and find services and/or products that fit the models discovered by data mining or complement them.

Common methods for recommendation models include content-based filtering, collaborative filtering, and hybrid system [22], and more recently, neural architecture-based systems and self-supervised learning to reduce the demand for labeled data [23].

E. Metaverse and VR design and implementation

Interaction within a virtual reality world can be described as simulating the interaction between the user and the real environment within a virtual 3D graphical environment [24]. If an interaction does not occur in reality, then to fit the user's mental expectations, it is better for the user to perform it in an unconscious state [25] called implicit interaction. In event-related scenarios, they must be associated with a specific event. For example, in the case of emotion-related EEG signals, using emotion-regulating psychological therapy [26] combining the VR scene with positive emotional arousal [27] as feedback when the user is experiencing negative emotions can be the appropriate solution.

III. Methodology

Overall, we have designed an autonomous treatment system that combines VR, EEG, emotional assessment, and feedback to the user through the Internet of Things framework. Fig. 1 shows the overall flow of the system. First, user EEG data is collected, analysed, processed, and imported into a training model. The above results are then transmitted via the user datagram protocol (UDP). In the VR scenario that we have built, the user is guided through the results and interacts with the scenario to obtain the corresponding treatment.

A. IoT and hardware connection

As shown in Fig. 1, the hardware comprises a VR headset and an EEG sensing device. The first step in the overall design of this system is to connect these two devices to a computer. To select the appropriate connection method, we first performed a requirement analysis.

Fig. 2: An example of a VR Head-Mounted Display (left) and an EEG headset (right).

Regarding the choice of connection method, cloud node-supported connectivity, which has been widely researched in the context of the Internet of Things, was once considered for use. However, in comparison, building a local IoT directly within a local area network not only requires lower power consumption and is more stable but also has greater privacy. The system we built is for self-help treatment of people with mental illness or high anxiety, and if the signals and analysis results were only stored locally, the data would be more protected. Therefore, we chose to use a local IoT to connect the devices.

B. Data-driven recommendation

As shown in Fig. 1, the data analysis part contains two stages: (1) The first stage is discovering general patterns from the benchmark dataset (more on this later) to identify users' characteristics on two distinctive mental states: high anxiety and low anxiety. The benchmark data set contains the class labels in these two states.

The second stage is to provide personalised recommendations. We would compare these patterns in real time to the EEG signals of an individual user to determine their current states, then recommend appropriate types of virtual content instead of setting the default to relax. With this approach, the appropriate stimulus from the recommended content would be able to rapidly guide the user from the current emotion to the target emotion. It could also help avoid unnecessary stimuli after the user reaches the target emotion.

C. EEG data analysis

EEG data or signals can be broadly analysed in three ways: (1) in the time domain, for example, to use the moving average; (2) in the frequency domain, for example, to use the Fourier transform [18] [28]; and (3) at the time-frequency domain [29] [30]. This work has chosen to carry out the data analysis in the time-frequency domain.

On the time-frequency domain, EEG signals often display different frequency characteristics at different moments. Only representing EEG data in either the time or frequency domain fails to capture the true characteristics of EEG signals. So, we consider the time-frequency domain to integrate both time and frequency. Time-frequency methods provide effective localised analysis in both time and frequency domains and possess additional significant properties, which make them widely applicable in EEG analysis [29] [30] [31]. Their advantages also include the ability to decompose signals into coefficients to represent scales, providing a mapping of a time domain function to a time scale function [32]. Among various time-frequency techniques, the simplest is the Short-Time Fourier Transform, which necessitates a trade-off between time resolution and frequency resolution. Currently, the most utilized time-frequency methods are the Wigner Distribution and wavelet analysis.

D. VR design

According to the definition of [25], the interaction with VR that uses EEG as input can be considered an implicit interaction. The user interacts without knowing the conditions under which the interaction occurs and then receives feedback from the virtual environment. However, implicit interaction can only be used to complement explicit interaction rather than by itself. Therefore, we need to add explicit interactions to the VR scene based on the information contained in the EEG signal. Since the EEG data used are classified in terms of human emotions, it can be judged that this is the ERP, and the relevant event is the level of anxiety. This information can be used to design interactions based on psychological therapy purposes [26]. Therefore, three different explicit interactions were introduced to implement three different psychological treatment protocols.

Communication has a good effect on the regulation of negative emotions. Inspired by the research conducted by [33], [34], which successfully provided psychological therapy to patients using an NLG model called ChatGPT, our aim is to assist in channelling user emotions in similar ways by allowing ChatGPT to communicate with users. Openai[1] provides an interface for developers to call the ChatGPT model in their code by entering a string into the interface, which then returns the text generated by the ChatGPT. This can

[1] https://openai.com/

be used to simulate a virtual counsellor in a virtual world. Google provides API Speech-to-Text to get the sound from the microphone in real time and send the sound into the speech transcription into text. For the construction of VR scenes, using Unity[2] will make it easy to build scenes and achieve different interactions.

IV. Experiments

A. Hardware and IoT

The hardware we used in this experiment was as follows:

- VR: Oculus Quest2
- EEG: Emotiv EPOC FLEX
- Laptop: CPU: Intel(R) Core(TM) i7-10875H CPU @2.30GHz, GPU: RTX2070, RAM: 16.0 GB.

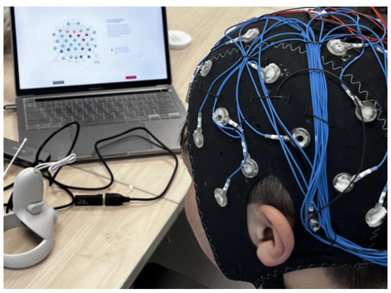


Fig. 3: EEG electrodes connection.

Our VR device of choice is the Oculus Quest2 because it is one of the most popular commercial devices in the market. The Quest2 is a portable wireless VR goggle that can also be used to import self-developed VR models for manipulation. So, we can use this VR HMD to deploy the autonomous diagnosis and treatment system we have designed. The EEG device that we have chosen is the Emotiv EPOC FLEX, a research-based overlay EEG headset with a large number of channels to ensure accurate and comprehensive EEG data acquisition. Furthermore, since it connects wirelessly, it does not interfere with the use of the VR device. Fig. 3 shows the connected channel nodes from which the EEG data will be collected.

During the experiment, we first helped participants wear EPOC FLEX and then confirmed the stability of the electrode connections for each channel. After confirming a good EEG connection, participants wore VR glasses. After the connections were made, the resulting setup is shown in Fig. 4. In particular, we specialised the use of the VR device. We use a cable to connect Quest2 to the computer to facilitate immediate debugging of VR HCI scenarios. In practise, we can package and import VR scenes into Quest2 for a completely wireless and portable design.

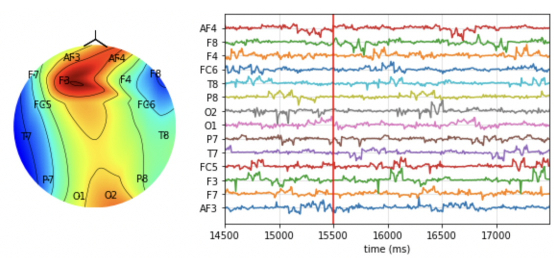
B. EEG data analysis

As discussed in Section III-B, before the experiments, we carried out the data analysis on the benchmark dataset [35]. The sampling rate is 128Hz. Each set of data was labelled

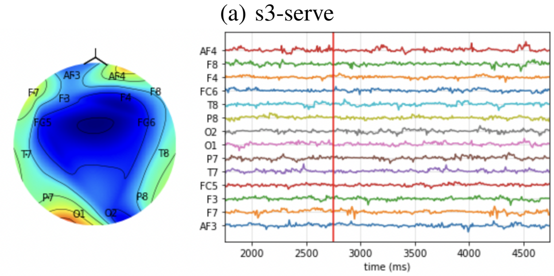
[2]https://unity.com/cn

Fig. 4: A user wearing the BMI setup that includes the VR HMD, the EEG device, and other equipment for interacting with the VR environment.

by the expert and participants according to their level of anxiety. During the experiments, real-time EEG signals were collected, as shown in Fig. 5. It shows the voltage values in mV (Millivolts) on the named electrodes. Fig. 5 illustrates the heat maps and readings according to time. The upper part shows a typical example of ‘severe anxiety, while the lower part shows a typical example of a “normal state”.



(a) s3-serve



(b) s10-normal

Fig. 5: Heat-maps and readings along the time axis. (top) an example of ‘severe anxiety’; (bottom) an example of ‘normal’. Data source [35]. The signals are in mV (Millivolts).

Wavelet analysis is conducted at the time-frequency domain, considering both domains at the same time, thus potentially avoiding the limitations of only considering one of them. Wavelet-based methods are well known for discovering how frequencies change over time. It is suitable for EEG detection because wavelet-based methods can associate spectral information to the time domain [36].

A signal can be represented or approximated by a family of functions that are constructed from scaled and translated versions of an appropriate mother wavelet. The resulting transformation coefficients are visualized in Fig. 6. EEG channel F3 is used here as an example. Their x-axis is time, measured in seconds. The total length is 30 seconds, which contains two different scenarios: the first one aimed to trigger anxiety lasting for the first 15 seconds and was classified by the medical expert as "severe anxiety" [35]. The second stopped the trigger, which lasted the rest of 15 seconds. At the y-axis level, the first row is the signal at the time domain. The following rows represent the resulting transformation coefficients using 7 different mother wavelets, including Gauss, Morlet, Gabor, and Poisson.

The transformation coefficients represent the EEG characteristics of a participant under different scenarios, which we use to determine the participant's mental states to make personalized recommendations. For example, when we detect a participant's EEG signals that demonstrate similar patterns to Fig. 6, our system would recommend VR scenes designed to relax the participant, such as displaying a meditation setting.

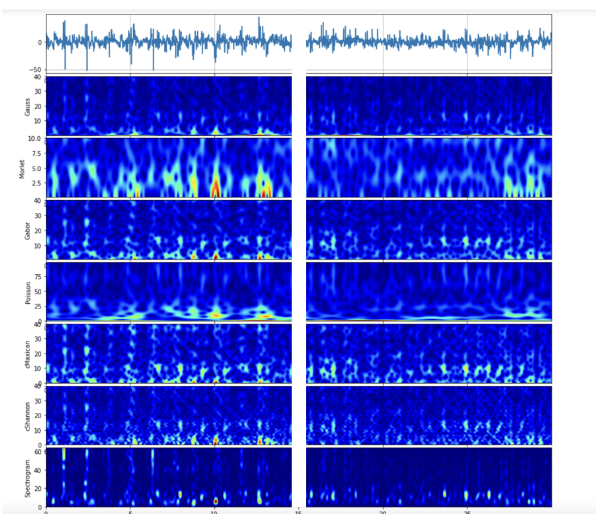


Fig. 6: The top row is the signal at the time domain. The rest of the rows are Wavelet transform. This shows the EEG channel F3 changes under two different scenarios for the participant ID S3 [35]. (left) trigger anxiety; (right) stop triggering anxiety.

C. VR scenes

To fit the different levels of mental states, we built four different scenarios to implement positive emotion arousal for the user: the controlled room, the meditation room, the chat room, and the explored room, which are shown in Fig. 7.

The control room is a room close to reality, set up like the living room of an apartment. The role of this room is to provide a transition space between reality and the virtual environment. Chat Room uses the previously mentioned ChatGPT interface, and users will talk to simulated people in the virtual environment through voice communication.

Some university students who were invited to try our prototype commented that the aforementioned scenes for meditation in VR allowed them to get into the state. Users could follow guided directions to practice meditation and thus achieve a relaxing effect. In addition, the VR of the forest as a virtual environment has positive emotional arousal.

V. Discussion and Conclusion

This paper presents a novel brain-metaverse interaction system that connects an EEG headset, AI data analysis, and a virtual world. This work enriches user experience in the virtual world. Furthermore, the reported work focuses on anxiety, but can be extended to other mental states.

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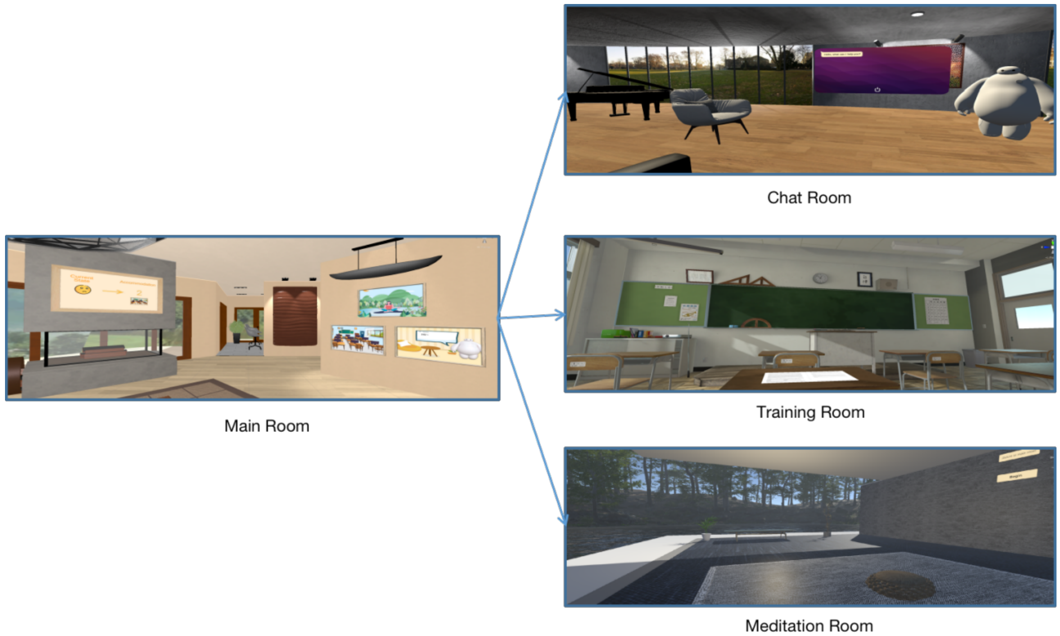

Fig. 7: The guide map of VR scene design. The main room is controlled, which can enter other rooms, and the last three of which are used to implement the positive emotion arousal therapy programme.

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