An Intelligent Agent-based Immersive Brain-computer Interface Prototype

ABSTRACT

Brain-computer Interface (BCI) has been adopted in virtual reality for active control and assistive monitor device for a long time. While limited light falls upon the potential of passive BCI as an intuitive interaction method. In this paper, we propose an agent controlled BCI-based Virtual Environment (VE). It bases on the passive BCI method and targets at changing mental state of people. Under the environment, the reinforcement learning (RL) agent reads and records the mind state of user and learn to change mind of user towards a pre-defined direction by changing the VE implicitly. During the process the VE evolves as RL agent learns from EEG feedback without active human effort. The system proposed a natural, intuitive application of passive BCI and justifies the adoption of BCI for healthy people. This opensource system is affordable for commercial VR users. And Preliminary test shows it is generally effective.

AUTHOR KEYWORDS

Brain–Computer Interface; Implicit Interaction; Virtual Reality; Reinforcement Learning;

ACM CLASSIFICATION KEYWORDS

H.5.2. User Interfaces: Interaction styles

H.5.1. Multimedia Information Systems: Artificial, augmented, and virtual realities

INTRODUCTION

Although the idea of reading Electroencephalogram (EEG) could be traced back to 1929 [21]. The concept of brain-computer interface (BCI) was not proposed until early 1970s [20]. Initially it was adopted to restore independence of people suffering from neural pathways diseases. Since it could bypass the normal output of brain such as peripheral nerves and read signals directly [22].

As the cost and complexity of BCI falls drastically In recent years, it has been freed from the original exclusive medical definition [22]. Instead of a “ non-muscular communication and control channel for neuromuscular disabilities” [21], BCI has expanded to serve the communication need of healthy people [22].

In recent decades research groups have been bridging BCI and virtual reality (VR) [9]. The purposes are: 1) using BCI as an input in virtual world and 2) using VR to provide safe experiment environment [3]. The adopt of BCI as input generally involves active input such as Motor Imagery (MI) [9]: People could be trained control objects [11] or navigate [6] in Virtual Environment (VE) via mental state. Besides, BCI researchers also endorse experiments conducted in VE for safety and flexibility reason.

Despite those accomplishments, there are several limitations about current BCI-VR system: 1) The method is still inherited from BCI for disability. It is not indispensable for healthy people 2) The active BCI requires an complex acquisition process [21] and training to maintain. Initially defined as a “skill”, it violates the natural, intuitive and easy to learn principle of interaction [10] 3) Multi-channel inputs are hard to handle. It is easy to press “A” and “UP” button at the same time on the game-pad, while almost impossible for mental state.

To solve the problems, we propose that the passive BCI should be adopted instead of its active counterpart in VR. Recent scholars propose the concept of passive BCI and classify brain-computer interface into three types: active, reactive and passive [22, 23]. Active BCI is the interface which is directly and consciously controlled by users. While passive BCI is the interface which changes in cognition resulting from interaction state without any additional effort. It is currently used for implicit HCI as an assistive parametric [18]. With several promising prototypes, scholars agree it has the potential as a new type of interaction [22].

In this paper, we describe a passive BCI-based interactive virtual environment. Instead of controlling avatars, the objection of interaction is mediating mind state of user without active control. It is composed of a virtual environment, a reinforcement learning (RL) agent and an EEG input device.

When interacting: 1) Initially, no instruction or training is needed. 2) During the process, the user does not intend to interact nor translate signals [22]. The multi-channel mind state of user (such as band power, emotion parametric) is captured by EEG device and recorded by RL agent. 3) The RL agent feedback to the virtual environment context at a predefined mental target (such as arousal up or alpha band-power down) 4) Synchronously, the RL agent update its policy function (the pattern of reaction to a certain state) towards the mental target.

Compared with current application of BCI in VR, our system 1) connects interaction with physiological or mental target (such as beta wave down) which could not be easily substituted by other inputs 2) proposes an application of BCI caters the need for natural, intuitive interaction in VR [10] 3) is able to handle multi-channel passive information although impossible for active information.

Then we produce two example scenes with the system. Preliminary user tests with example scenes suggest that although varies from people to people, the system is generally usable and effective.

CONTRIBUTIONS

- Design considerations for integrating BCI into commercial VR devices

- Bridging method of passive BCI with mentally meaningful target in a virtual environment

- An opensource platform integrating BCI and RL algorithm for community development

- Verification the effectiveness of RL algorithm and virtual environment in mediating mind state of people

RELATED WORKS

Else than passive Brain-computer Interface, this system is also related to 1) the method of mindfulness training 2) the application of brain-computer interface in virtual reality

**-****Technology Supported Mindfulness Training**

From another perspective, increasing attention falls upon mindfulness training (MT) [14, 16] over the last two decades. Although scholars agree that the reliability of Mindfulness-based Mobile Applications (MBMAs) in market is susceptible [13, 16]. The overall effectiveness of MT meditation method is endorsed [5].

Despite the endorsement, those wholesome materials are usually created empirically by designers according to previous cases or principles. There are two major limitations: 1) The design process itself is complex and ineffective: through a design cycle “” 2) The result could contain bias of designers and blindside is hard to uncover: since the traditional MT principles are testified as most effective and neurofeedback-design is inaccessible to general practitioner [4].

To solve this problem, the reinforcement learning should be used as neurofeedback.

**-Brain-computer Interface in Virtual Reality**

One of the pioneer research is conducted in University College Dublin, where users could mind-balance an avatar (1 dimension) [8]. Complex controls through MI include car driving (2 dimension) [17] or character manipulating (3-5 dimension) [12] have been proved robust [19]. Since that, VR community deems BCI as an assistive and intuitive input device for VE interaction.

VR is widely used for scenario simulation. One of the classic study in Graz University of Technology build a system testing for BCI controlled wheelchair [17]. Clearly Virtual Reality simulates rich aspects of physical environment except car crash. Moreover, evidence shows that immersive environment is more effective than boring 2D visual stimuli [2]. Since the users are more motivated in VE, the response delay and error rate decline.

Despite those attempts

Machine learning algorithms are widely adopted for both active and passive BCI. The difference is: 1) the active BCI adopts classification [] or regression [] to recognize mental command, the passive BCI adopts reinforcement learning either policy based (Policy Gradient), or value based (Function Approximation), or both (Actor-Critic) 2) the training procedure of active BCI is prior to interaction process, the training procedure of passive BCI is synchronized with interaction process 3)

Early researchers propose that EEG alpha (8-13Hz) band power and its variance, include upper-alpha wave [24] and individual alpha frequency (Klimesch, 1999), could be used as the indicator for p

Previous study proposes that Alpha (8-13 Hz) is dominant during flowing thought and meditation.

Higher alpha EEG activity is more associated with relaxed conditions than with states of stress

Investigations of human EEG response to viewing fractal patterns

International 10-20 system (Investigations of human EEG), different areas: frontal, parietal, temporal, sensory info is precepted and modified by parietal and temporal regions. While frontal area is more significant to visual stimuli

The concept of this system built upon the passive BCI

And previous positive result

DESIGN CONSIDERATION

**-System Structure**

The system is composed of 4 parts: Unity platform, Oculus VR device, OpenBCI EEG device and Tensorflow agent.

The Unity platform runs as the server, rendering the frames directly to Oculus VR headset and to monitor. The OpenBCI EEG processing software and Tensorflow agent run as the client. The data is streamed using UDP with OpenBCI and TCP with Tensorflow. since the former one requires less delay and the later one needs precision.

The Tensorflow agent controls model-updating and rendering step. While OpenBCI runs asynchronously and broadcasting EEG data at a higher frequency.

The Tensorflow agent record the EEG state, evaluate

and send action [] to the unity server. And the server updates the environment in Oculus VR.

The render frame is controlled by the Tensorflow agent

**-Electrodes Selection**

Due to the shape of VR device, the Fp, O and AF areas of the 10-20 Electrodes system is occluded by mask. Some study [7, 15] suggest that the Fp and AF Electrodes are more relevant to facial muscle movement instead of neural activities. And More detailed research also revealed the correlation of specific emotion with the band power of a specific Electrodes. [7]

These evidences suggest that the current electrodes map is adequate for the research purpose.

**-Low-cost and opensource**

The complicated headset with 54 or 64 Electrodes used to be widely adopted in EEG-related research [?]. These devices far are more expensive than VR device itself. While research show that device with 5-6 channels could produce decent accuracy in emotion related brain activity (SSVEP) [1]. And more complicated devices fit event-related signals (P300).

To shirk the cost, 8-Channel opensource OpenBCI Board is chosen as the start point. Since motion capture and data stream is built already, accelerometers and SD card are removed. The weight of 3D-printed headset is lightened to a half for Oculus CV while 23 out of 35 Electrodes slot is kept. Except the free-to-use unity3D Engine, all the software required to run and develop this system is opensource.

Suitable for VR; Channels; Availability; price = X Oculus CV 1

Our Device (Forked from OpenBCI) Yes; 8 of 23 Locations; price = 0.625 \* Oculus

Neurable Yes; 7 Channels; Not available Yet; No price info

Emotiv insight No; 5 Channels; Price = 0.75 \* Oculus

Original OpenBCI No; 8 of 35 Locations; Price = 1.25 \* Oculus

Emotiv Epoch+ No; 14 Channels; Price = 1.99 \* Oculus

Biosemi Yes; 16 of 256 Locations; Yes; Price = 40.5 \* Oculus

NeuroScan Yes; 64; Price = 231 \* Oculus

Table X. the cost of popular EEG devices

Compared with other device, the price of our device is reasonable for commercial VR users. It promises the freedom for community development and flexibility for researchers.

IMPLEMENTATION

**- System Specification**

Due to the rendering and calculation load, the Unity server is deployed on a data station with 2 NVIDIA TITAN X Graphics Card. The framework of agent is Tensorflow GPU r1.2. Other environment configuration includes Python 3.5.2, CUDA Toolkit 8.0 GA2, cuDNN v6.0 (April 27, 2017) and Windows 10.

The EEG data is acquired @250Hz by OpenBCI Cyton board. Raw data is filtered to 1-50Hz and Fast Fourier transformed (FFT) into EEG band power: Delta wave (0.5–3 Hz), Theta wave (4–7 Hz), Alpha wave (8–13 Hz), Beta wave (16–31 Hz) and Gamma wave (32–50 Hz). The band power data is send to UDP server in Unity and streamed in hard drive for future analysis.

Run at different pace

**- Anatomy of One Loop**

**-Example 1**

**-Example 2**

EVALUATION

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