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). 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. While it could relief people’s stress or enhance brain activity. This system is affordable, opensource and generally effective.

AUTHOR KEYWORDS

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

ACM CLASSIFICATION KEYWORDS

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

INTRODUCTION

As cost of Brain-computer Interface falls drastically, the BCI has been freed from exclusive medical use. More attention falls upon the need of healthy people instead of disabilities [].

The BCI expands to healthy people [20] as the cost lower. The need for MI declines as emotion tuning increase.

For passive BCI is rare. The potential of passive BCI:

More natural and Intuitive than other methods: people could immerse themselves into the process without active behavior.

For this reason

From another perspective, increasing attention falls upon mindfulness training (MT) [13, 15] over the last two decades. Although scholars agree that the reliability of Mindfulness-based Mobile Applications (MBMAs) in market is susceptible [12, 15]. 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.

The aim of this system is 1) to propose a new possibility of BCI-based virtual reality interaction 2) to expand the application of passive Brain-computer interface by integrating reinforcement learning agent into the interaction process and 3) to facilitate a opensource platform enabling the agent-based design of interactive virtual environment (VE) suitable for neurofeedback-assisted mindfulness training or other emotion regulation.

The Reinforcement learning agent could provide a search tree

Mindfulness training

Mobile App

Non active, Implicit Interaction

Feed back intelligently

The EEG parametric

We modify OpenBCI- with Oculus CV1

Selected from a standard 10–20 system

Early researchers propose that EEG alpha (8-13Hz) band power and its variance, include upper-alpha wave [22] 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

RELATED WORKS

The concept of this system built upon the passive BCI

And previous positive result

**- Passive BCI**

Recent Scholars classify Brain-computer Interface into three types: active, reactive and passive [20, 21]. Passive BCI is the interface which changes in cognition resulting from interaction state without any additional effort. And it is used for implicit interaction in HCI [17].

A mouse move controlled

Passive BCI initialized to be secondary [18] input for primary interaction

One research on passive BCI

While quite primitive

EEG is commonly used as a

benchmark

**-BCI-based Virtual Reality**

In recent decades research groups have been bridging Brain-Computer Interface (BCI) and Virtual Reality (VR) [9]. The purposes are 1) using BCI as an input in virtual world and 2) using virtual reality to provide safe experiment environment [3].

The adopt of active BCI in VR generally involves Motor Imagery (MI) [9]. People could control objects [10] or navigate [6] in Virtual Environment (VE) via mental state. To connect mind and command, an individual training session is required. 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) [16] or character manipulating (3-5 dimension) [11] have been proved robust [19]. Since that, VR community deems BCI as an assistive and intuitive input device for VE interaction.

On the other hand, BCI researchers endorse experiments in VE for safety reason. Historically, BCI research is for prosthesis control and motor substitution for disables [9]. 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 [16]. 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.

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, 14] 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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