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Study on Robot Grasping System of SSVEP-BCI Based on Augmented Reality Stimulus

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Abstract: Although notable progress has been made in the study of Steady-State Visual Evoked Potential (SSVEP)-based Brain-Computer Interface (BCI), several factors that limit the practical applications of BCIs still exist. One of these factors is the importability of the stimulator. In this study, Augmented Reality (AR) technology was introduced to present the visual stimuli of SSVEP-BCI, while the robot grasping experiment was designed to verify the applicability of the AR-BCI system. The offline experiment was designed to determine the best stimulus time, while the online experiment was used to complete the robot grasping task. The offline experiment revealed that better information transfer rate performance could be achieved when the stimulation time is 2 s. Results of the online experiment indicate that all 12 subjects could control the robot to complete the robot grasping task, which indicates the applicability of the AR-SSVEP-humanoid robot (NAO) system. This study verified the reliability of the AR-BCI system and indicated the applicability of the AR-SSVEP-NAO system in robot grasping tasks.

Key words: Steady-State Visual Evoked Potential (SSVEP); Brain-Computer Interface (BCI); Augmented Reality (AR); robot; grasping system

1 Introduction

Brain-Computer Interface (BCI) is a technology that detects the brain's intentions and converts them into computer instructions. In a typical BCI paradigm, Steady-State Visual Evoked Potential (SSVEP)-BCI is preferred by scholars due to its remarkable advantages of better Information Transfer Rate (ITR), larger Signal-to-Noise Ratio (SNR), easier quantification, and less training[1–5]. SSVEP is regarded as a periodic electrical signal that is evoked by a visual stimulus at a specific frequency and is mainly distributed in the occipital region[6]. In traditional SSVEP-BCIs, all the targets flicker with different frequencies, and the gazed target is determined by identifying the SSVEP frequency[7, 8]. In recent studies, advanced coding and decoding methods have been applied to improve the performance of BCIs.

Although notable improvements have been made in the performance of BCIs, several factors that limit the applicability of BCIs still exist. One of these factors is the importability of the visual stimulation device. In traditional SSVEP-BCIs, a Liquid Crystal Display (LCD) screen is used to present visual stimulation, and subjects are required to sit flat in front of the stimulation interface and switch their eyes between the stimulator and the test environment. However, given the limitation added by the inclusion of the screen, the SSVEP system was considered a non-portable system. As a result, many researchers began to look for strategies to eliminate

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the fixed visual stimulators. Fortunately, it was found that combining Augmented Reality (AR) devices with brain-computer interfaces can reduce the complexity of the system and further improve the ease of usage and applicability of the system[9, 10]. AR combines reality with the virtual world in such a manner that subjects could interact with the virtual world to achieve a sensory experience that transcends reality.

In this study, we designed an AR-BCI system to improve the importability problem of the stimulators in BCIs, in which AR provided a visual stimulation of SSVEP and presented a virtual visual stimulation interface to the subjects. In fact, studies on AR-BCIs have been conducted, and some valuable results have been obtained. For instance, scholars[11] designed an AR-BCI system that captured the AR mark using a robot camera and transmitted it to the screen for the control of a desk lamp. In addition, researchers wore a camera to capture and identify the AR mark and generate a BCI visual stimulation control panel to control a desk lamp or television[12]. For instance, Horii et al.[13] mapped the captured realistic scene and SSVEP visual stimulation to the human eyes using a head-mounted displayer. Wang et al.[14] verified that holographic glasses were able to induce stable SSVEP signals, and the accuracy was 83.85% for the data length of 1 s. The aforementioned studies verified the applicability of AR-BCI; however, more complex application scenarios need to be further explored.

Humanoid robots can help people complete tasks intelligently in a complex environment[15, 16]. This made the study of humanoid robot applications based on brain-computer interfaces very important[17]. For instance, Spataro et al.[18] designed a BCI system to control the robot to grab a glass of water in order to assist those suffering from serious diseases rather than relying on caregivers. Chae et al.[19] used the Motor Imagery (MI)-based BCI system to create the robot's navigation in the indoor maze. Duan et al.[20] designed a hybrid BCI system that uses three SSVEP commands to control the robot to walk as well as one MI command that controls the robot to grab colored objects. While most of these previous studies were based on the traditional BCI systems, studies on the application of AR-BCI-based robots are sparse.

In this study, we designed an AR-SSVEP-humanoid robot (NAO) system to investigate the applicability of BCIs. The AR-SSVEP maps the collected electroencephalography (EEG) signals into instructions to control external devices to complete tasks. The multi-sensor fusion NAO was introduced to verify the reliability of the AR-BCI system. Using the designed AR-SSVEP-NAO system, subjects were required to control the external equipment (NAO) to complete complex grasping and placement tasks. The applicability of the system was verified by the offline and online experiments.

2 Materials and Methods

2.1 Subjects

Twelve healthy subjects (4 females and 8 males; age range: 21–27 years) with normal or corrected-to-normal vision participated in this study. All the subjects participated in both the offline and online experiments. After understanding the experimental process and precautions, each of the subjects signed informed consent prior to the commencement of the experiment and received monetary compensation for participating in the study. This study was approved by the Research Ethics Committee of Tsinghua University.

2.2 Visual stimuli in AR

In this study, we used HoloLens as the AR equipment to present visual stimuli. The HoloLens was a wireless head-mounted augmented reality glass from Microsoft. The Holographic Processing Unit (HPU) was a customized dedicated chip integrated into the small-volume glass, which could combine the real environment with virtual objects to give the wearer access to a peculiar world environment.

The visual stimuli in the AR were produced by Unity3D and Visual Studio 2017 and fixed in front of the subjects to ensure that the experimental scene was observed and noticed. Eight targets were presented in the visual stimuli interface with the stimuli frequencies of 8 Hz (R1), 9.5 Hz (B2), 11 Hz (P3), 8.5 Hz (Le4), 10 Hz (Fo5), 11.5 Hz (Ri6), 9 Hz (P7), and 10.5 Hz (S8), respectively. In the online experiment, each target corresponded to a specific operation command. Specifically, R1, B2, and P3 represented the recognition and tracking of the red, blue, and purple balls, respectively. Le4, Ri6, and Fo5 indicated a 45° left turn, 45° right turn, and forward command, respectively. P7 encoded the command to put the captured ball into the designated area, and S8 encoded the command to stop the current action. The eight stimuli blocks on the visual stimuli interface were not uniformly distributed (see Fig. 1). They were arranged in three rows, in

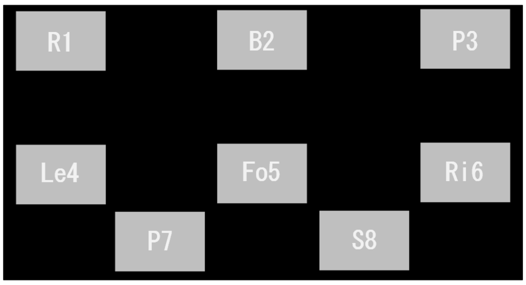

Fig. 1 Spatial distributions of AR stimulus.

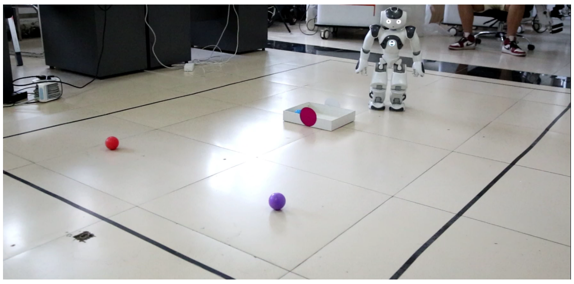

Fig. 2 Experimental environment.

which the first and second rows contained three stimuli blocks, and the third row contained two stimuli blocks. During the experiments, the visual stimulus interface was mainly presented on top of the robot, and the design of the stimuli interface was mainly to ensure a more convenient and easy way of controlling the robot.

2.3 Data acquisition

The Neuracle EEG Recorder (Neuracle, Inc.) was used to acquire EEG data at the sampling rate of 1000 Hz. The data were down-sampled to 250 Hz and band-pass filtered from 1 to 100 Hz. EEG data were recorded at the nine electrodes (Pz, PO5, PO3, POz, PO4, PO6, O1, Oz, and O2) in the occipital region, and the reference electrode was located at the vertex. All electrodes were placed according to the international 10–20 EEG system. Electrode impedances were kept below 10 kΩ. The recorded EEG data were uploaded to PC via WIFI using a wireless amplifier, and a photoelectric sensor was used to synchronize the visual stimuli and EEG data. During the experiment, the synchronizer sent a trigger to the EEG recording software, which in turn marked the trigger on the collected EEG data.

2.4 NAO robot system

The external equipment used for this research was the humanoid robot NAO. NAO was developed by Aldebaran Robotics and is widely used in competitions, education, and scientific research. NAO had 25 action freedoms in the whole body, with three touch sensors on top of the head and two complementary metal-oxide semiconductor cameras on the head and mouth. NAO uses monocular vision and the cameras cannot be called simultaneously. We designed two online tasks for the robot: walking in a certain area and tracking and grabbing a target object. Afterward, we placed the object in the designated position.

Figure 2 reveals the online experiment environment. The experimental area was the rectangular region with the black line border. The size of the rectangular was 250 cm × 150 cm, and the distance between the balls or robot and the nearest two sidelines was 25 cm. Subjects were required to control the robot to grasp three balls (blue, purple, and red) on the ground to the designated area. The three balls (having a diameter of 5 cm each) were placed at the three corners of the rectangular area, and the robot was placed at the fourth corner. First, the robot recognized the captured ball in its visual field and measured the distance using the monocular measurement model. Second, the robot continuously adjusted its posture to track the target and approach the target as well as squat down and recognize the target again. Third, the coordinates of the ball relative to the camera were converted into coordinates relative to the robot. Using robot kinematics, the end effector of the arm was controlled to the desired position for grasping. After grasping the ball, subjects were instructed to control the robot to approach the placement area and drop the ball. In each experiment, the robot needs to grab each of the three balls and put them in the placement area.

2.5 System communications

The communication between the wireless amplifier, PC, NAO, and synchronizer was done under the same local area network (LAN). The data acquisition system and the NAO system worked on the same PC and were developed with MATLAB and Python, respectively. TCP/IP was used to transmit data between programs. EEG data were processed in MATLAB, and the results were sent to Python and further converted into different tasks of the robot. The running time and transmitted data of the robot system were recorded by Python.

2.6 Data analysis

Considering a latency delay in the visual system, in the classification algorithms, a 140 ms delay was selected according to a previous study[4].

The Filter Bank Canonical Correlation Analysis (FBCCA) classification algorithm was used to identify the observed flicking target. In the processing of FBCCA, SSVEP is decomposed into sub-band components by filter banks; and then the conventional CCA analysis was performed. For details of the algorithm, see Ref. [6].

3 Offline Experiment

3.1 Experimental settings

The offline experiment included the systems of AR and BCI only (i.e., excluding the NAO system). The equipment used included: AR glasses, 64-lead EEG cap, Neuracle wireless amplifier, wireless router, synchronizer, and Window10 laptop. All the equipment worked under the same LAN. The AR glass was used as a visual stimulator to evoke EEG. The EEG cap was used to collect EEG data. The wireless amplifier amplified and transmitted the EEG data to the PC. A photoelectric sensor was used to synchronize the trigger and EEG.

Subjects need to wear the AR equipment to complete the offline experiment (see Fig. 3), in which the stimuli interfaces contained eight targets, as shown in Fig. 1. The brightness of the stimulation interface was adjusted to the maximum to reduce the influence of light in the environment. The offline experiment contained six blocks, which included 24 trials, while each of the 8 targets randomly appeared thrice. The prompt sounds "1", "2", "3", "4", "5", "6", "7", and "8" were used to remind subjects about the target they should focus on. The prompt sound (1 s) was followed by a response time (0.5 s), and the SSVEP visual stimuli (5 s) were presented. At the end of each SSVEP stimulation, another prompt of "Di" was used to remind the subjects of the end of the trial. The subjects were allowed to rest until the beginning of the next trial. The subjects were given the liberty to decide the rest time based on their situation.

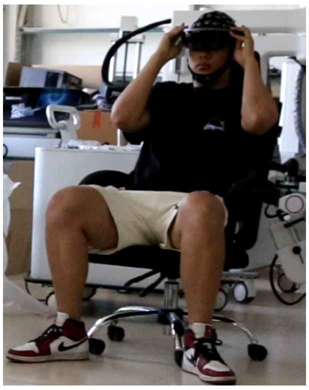

Fig. 3 A subject wearing the AR equipment.

3.2 Results

Figure 4 reveals the accuracy of each subject in the offline experiment. The EEG data of all 12 subjects were analyzed. The EEG data were first segmented according to the triggers and then preprocessed and processed by the FBCCA algorithm. All accuracies increased with the time length (data length) and tended to have a stable value. The results reveal that all the subjects achieved high accuracy using AR as a visual stimulator of SSVEP. For instance, when the time length was 5 s, the accuracies of all 12 subjects reached more than 95%, and the accuracies of 8 subjects reached 100%.

The averaged accuracy and ITR were also presented, as shown in Fig. 5. Figure 5a presented the relationship between the averaged accuracy and time length, which showed similar results with Fig. 4. Figure 5b showed the

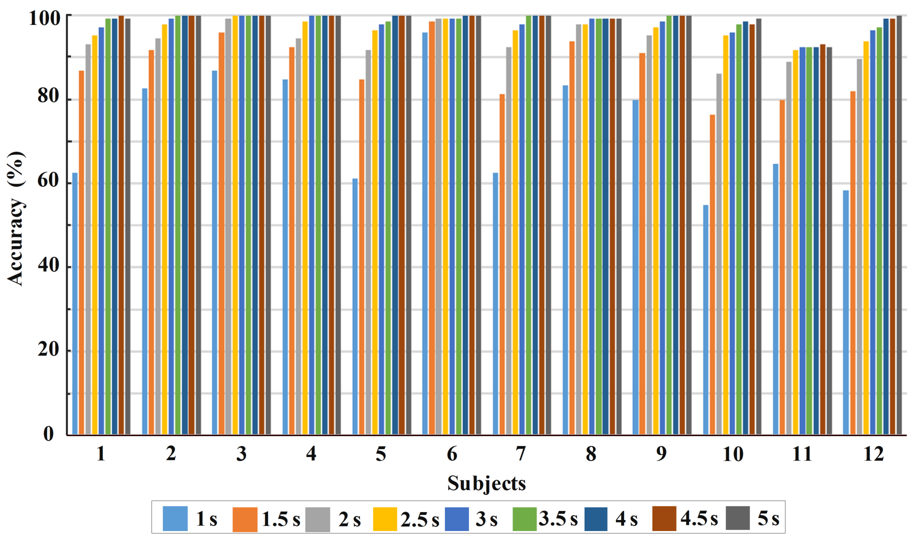

Fig. 4 Accuracy for each subject in the offline experiment.

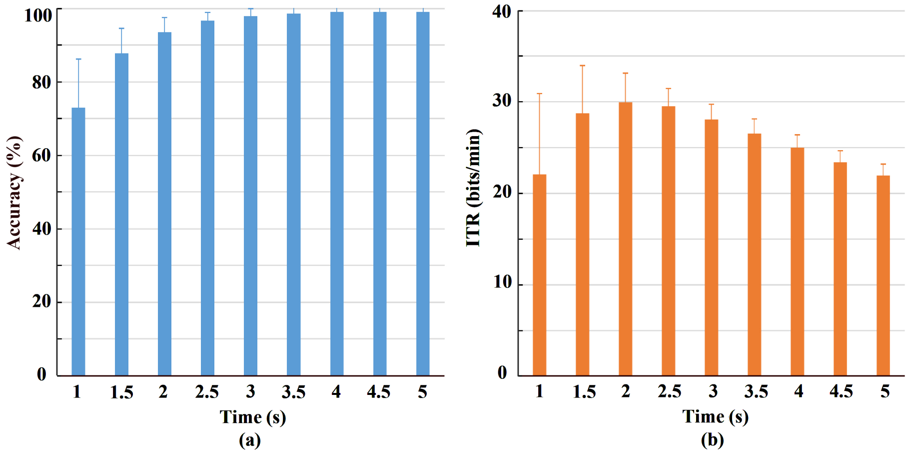

Fig. 5 Average performance of all 12 subjects. (a) Accuracy and (b) ITR.

changes of ITR with time. The values of ITR reached a maximum (30.32 bits/min) when the stimuli time was 2 s, and the corresponding accuracy was 94.05%. When the stimulation time was short (<2 s), the value of ITR increased with the stimulation time. When the stimulation time is long enough (>2 s), the classification accuracy tends to be stable, and the value of ITR decreases with the stimulation time.

The offline experiment verified the stability of the BCI system, indicating that better ITR performance could be achieved when the stimulation time is 2 s. Next, the NAO robot was involved in verifying the performance of BCI in the online system.

4 Online Experiment

4.1 Experimental settings

The online experiment was divided into two parts, the random prompt experiment and the autonomous selection experiment, which included and excluded the robot, respectively. The time length of visual stimuli was set to 2 s, which corresponded to the maximum ITR in the offline experiment.

In the random prompt experiment, PC gave the prompt sounds “1”, “2”, “3”, “4”, “5”, “6”, “7”, and “8” randomly to remind subjects of which target to gaze. After the voice prompt, there was a response time that lasted 0.5 s. At the end of the SSVEP stimuli, the reminder prompt sound “Di” is produced. If the subject chooses the right choice, a feedback prompt sound of “Da” would be produced. Each block contained eight trials, and each target appeared once randomly in a block. Each trial lasts 5 s, including rest time (3 s) and stimulation time (2 s). The random prompt experiment contained three blocks, which sum up to a total of 24 trials.

In the autonomous selection experiment, subjects controlled the NAO robot to track and grab the target until all three balls were placed in the designated region. The virtual interface was combined with the real environment, and subjects did not need to constantly adjust the head to observe the environment and interface (Fig. 6). Once one block was completed, the robot was allowed to rest for 5 min to cool its motor. Each subject was required to complete a total of three blocks of the experiment, and the system running time and detailed instructions were recorded by the PC terminal.

4.2 Results

Figure 7 shows the results of the random prompt experiment. According to the results, excellent performance has been achieved. The average accuracy of the 12 subjects was 95.83%±5.10%, while the average ITR was 32.21±4.35 bits/min. Notably, six subjects achieved an accuracy of 100% among the 12 subjects, and only one subject achieved an accuracy lower than 90%.

Figure 8 shows the results of the autonomous selection experiment. The average execution time was 689.2±30.63 s, and the average number of instructions

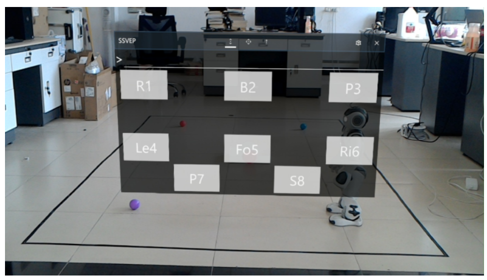

Fig. 6 AR controlling perspective.

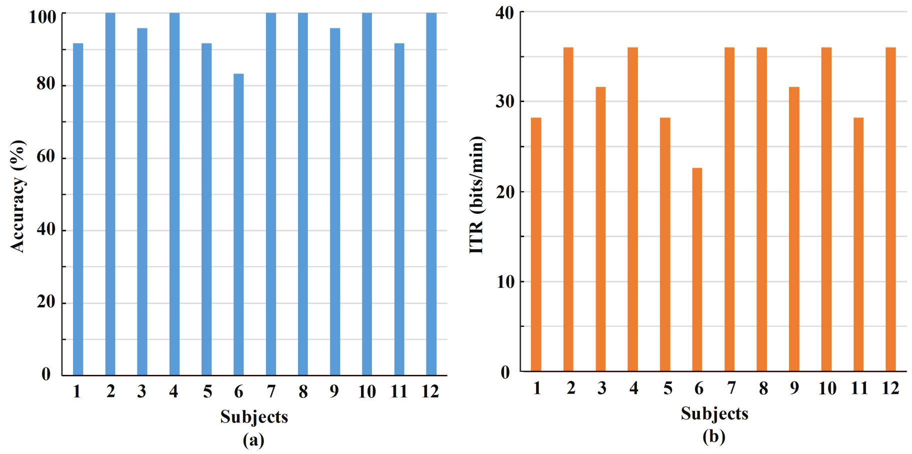

Fig. 7 Results of the random prompt.

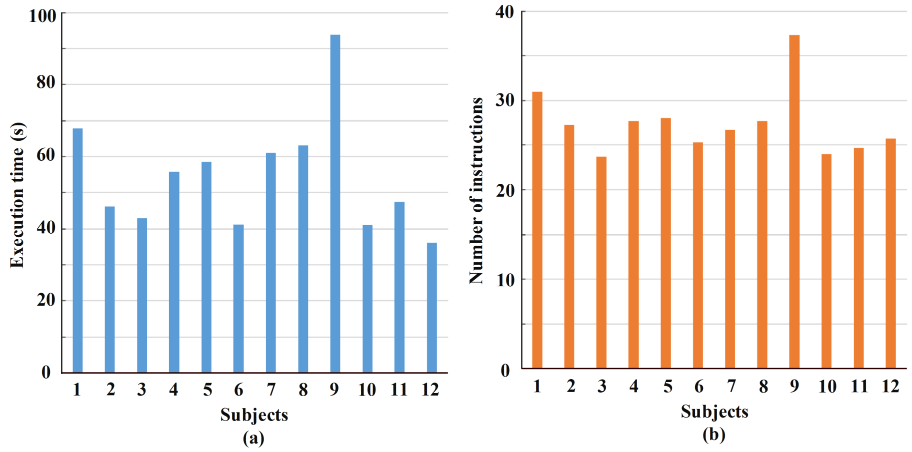

Fig. 8 Results of the autonomous selection.

was 27.4±3.56. It can be seen from Fig. 8 that the average control time of some subjects was longer and that there was a higher number of instructions. The experimental task of the online system was complex, and the subjects needed to focus on the stimulus interface. If the fixation was wrong, the subjects are required to re-select the flashing target to complete the subsequent tasks. The results indicate that all 12 subjects could control the robot to complete the grasping task and that the applicability of the system has been verified by the online experiment.

5 Discussion

The practical applications of the brain-computer interface are restricted by several factors. The search for suitable application scenarios for BCI has long been a challenge encountered by scientists in the field of neuroscience. To deal with the non-portability of the traditional BCI stimulators, this study introduced AR technology into the BCI system in order to make the BCI system more flexible. The experimental results of robot grasping verified the applicability of the combination of AR technology and BCI, in which all subjects are able to use the AR-SSVEP-NAO system to complete complex grasping tasks. The conclusions of this paper provide a new insight development of future portable BCI systems.

Although positive results were obtained, the system still needs to be improved in the following aspects: First, subjects only made decisions based on the scene within the field of vision. In order to improve the application scopes of the scenes, an external camera could be connected and transmitted to the PC so that the subjects could observe the scene remotely, thus improving the practicability and convenience of the system. Second, the intelligence of robots needs to be improved. In this study, the robot used a monocular vision for target recognition, which resulted in a recognition accuracy that is not as good as that of a binocular vision. With binocular vision, the robot could obtain the three-dimensional coordinates of the object. Third, the background anti-interference ability of the AR equipment HoloLens needs to be improved so as to improve the performance of the AR-BCI. These perspectives of the AR equipment need to be improved, considering that the subjects could not see the current interface when moving in a large range. In addition, the AR equipment was heavy and difficult to use for a long time, and this consequently made the subjects tired during the experiment.

6 Conclusion

In the traditional SSVEP-BCIs, subjects received visual stimuli from fixed stimulators, such as LCD screens, which made the BCI system non-portable. In this study, augmented reality technology was introduced to present the visual stimuli of SSVEP-BCI, and the robot grasping experiment was designed to verify the applicability of the AR-BCI system. The offline experiment was designed to determine the best stimuli time, and it was found that a better ITR performance could be achieved when the stimulation time is 2 s. The online experiment was used to complete the robot grasping task, and the results indicate that all 12 subjects could control the robot to complete the robot grasping task. This study verified the applicability of the AR-BCI system and indicated the feasibility of the use of the AR-SSVEP-NAO system in the robot grasping tasks.

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