Design and Implement the Continuous Flickering SSVEP-BCI in Augmented Reality

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Abstract. Brain-computer interface (BCI) provides a new way to express our minds without peripheral nerves and muscles [1]. In this work, a process control recognition method based on continuous flickering is proposed to output continuous commands. Phase matching method was applied in this work, matching the test data with the template with the same phase to improve the accuracy. We also put forward a high tolerance criterion and give a new definition to the recognition result of attention shift period. We first conducted a screen-based continuous flickering feasibility verification experiment using correlation component analysis algorithm (TRCA) method, and the recognition accuracy reached 85% and 90% under high tolerance criterion. The average offline simulation information translate rate (ITR) was 455.8 bit/min, and the highest ITR reached 524.7bit/min, which certificated the feasibility. Furthermore, we carried out a drone control experiment based on augmented reality (AR)-BCI using extended filter bank canonical correlation analysis (extended-FBCCA), and achieved an average accuracy of 90% and ITR of 49.1 bit/min, having better performance than repetitive visual stimulus (RVS) with intervals.

1. Introduction

Brain-computer interface (BCI) provides a new way to express our minds without peripheral nerves and muscles [1]. At present, the application of BCI in medical treatment includes assisting, enhancing and repairing the human body’s cognitive and motor senses and other neurological functions [2, 3]. In the future, brain-computer interface is expected to be widely used in people’s daily life, not only helping the disable people to achieve the movement, but also expanding the means of expression and bringing great convenience to people’s life.

Steady-state visual evoked potentials (SSVEP)-BCI system presents subjects with multiple repetitive visual stimulus (RVS) with different frequencies and initial phases. When subjects focus their attention on one of the RVS, SSVEP signals will be induced in the primary visual cortex, and the frequency components mainly include the corresponding visual stimulus frequency and its harmonics. By
identifying the SSVEP frequency in EEG signals, the target that the subject is focusing on can be identified, and then the subject’s intention can be identified.

At present, brain-computer interface systems mainly convey subject’s intentions in two ways: process control and target selection. In process control mode, the system controls every movement of the machine, thus requires high-speed recognition to complete the task efficiently and smoothly. In objective control mode, the system only needs to recognize subject’s order, and automatically realize the subject’s order (like the whole process of fetching a cup). The advantage of process control mode is that it allows the subject to achieve more flexible movement, various actions as he wishes, just like controlling his own limbs.

At present, the SSVEP brain-computer interface usually adopts the mode of RVS with intervals. This mode can accomplish the task well in the objective control mode, but it is difficult to realize high ITR in some process control situations where continuous object movement is required. Continuous flickering SSVEP means that SSVEP stimulus no longer flicker with intervals, it is continuously performed and synchronized in real time with the online recognition system, which continuously classifies and identifies the EEG signals and outputs the commands. In 2018, Zhang et al. realized a wearable SSVEP-based BCI system for quadcopter control using continuous flickering mode, and achieved the ITR of 4.6 bit/min with the method of CCA [4]. In 2019, Zhang et al. used filter bank canonical correlation analysis (FBCCA) to achieve 85% classification accuracy in movement control on screen [5]. In 2016, Kalunga et al. used Riemannian geometry to achieve the accuracy of 90%, and ITR of 16.3 bit/min, in which case of distinguishing only 3 different frequencies in their work [6]. In the existing studies, the ITR is not sufficient for smooth control and the implementation of high ITR can bring people a better human-computer interaction experience.

SSVEP based on computer screen can only be performed in laboratory, however augmented reality (AR)-BCI is portable and can be performed outdoors. In this work, a continuous flickering stimulus SSVEP system was explored, including visual stimulation, time synchronization and recognition methods. Feasibility verification of continuous flickering SSVEP-BCI system based on screen was performed first, and then performed the application of continuous flickering SSVEP method in AR-BCI. Continuous flickering SSVEP system is expected to improve the ITR, to improve the performance of brain-computer interface for process control, and further promote BCI to life.

2. Methods

2.1. Experiment

There were two experiments in this work. Five participants, including three males and two females, aged between 22 and 26 with normal vision or corrected to normal vision participated in both experiments. Eight electrodes (POz, PO3, PO4, PO5, PO6, Oz, O1, O2, distributed in 10-20 international system) were used. Top head was used as reference. All of the electrodes impedance was below 20 kΩ.

2.1.1. Experiment 1. The first experiment was done to show the feasibility of continuous flickering SSVEP. Visual stimuli were generated through Psychtoolbox. And the visual stimulation in the training stage is shown on figure 1a. Eight white circles flashed at 8 Hz, 9 Hz, 10 Hz, 11 Hz, 12 Hz, 13 Hz, 14 Hz and 15 Hz respectively, and their initial phases were 0 π, 1.75 π, 1.50 π, 1.25 π, 1.00 π, 0.75 π, 0.50 π and 0.25 π. A cross would cue subject the circle that he needed to focus. Each trial consisted of 0.5 second cue and 2 seconds stimulation. Each block was consisted of 40 trials; each participant completed the 5 blocks for training.

Figure 1b shows the visual stimuli in the online test. The visual stimuli were consistent with the stimuli used in training. Once the program started, each visual stimulus kept flashing. The trial switching did not reset the phase. A green cross would appear at the centre of the visual stimulus circle in each trial cueing the subject to look at. The duration of each trial was random, between 1.5 seconds and 2 seconds. Subjects immediately shifted their attention as the position of the green cross changed. Each block contained 16 trials. Each subject completed 5 blocks for testing.
2.1.2. Experiment 2. We used DJI Tello drone and HoloLens to put up the system and the visual stimulation program was written in Unity3D. The visual stimuli of training stage are shown in figure 1c. Each trial was consisted of 1 second cue and 2 seconds stimulation. The frequency and phase were shown in figure 1c (not to the subjects). Each subject needed to complete 10 blocks (80 trials) for training.

AR-BCI online control drone experiment included continuous and interval RVS control experiments. Frequency and phase were consistent with figure 1c. In the interval stimulus control experiment, four dark red squares with one white cross (on one of them) lasted 1 second to cue subjects to focus and then bright red squares flickered 2 seconds. In the continuous stimulus control experiment, white cross moved among 4 squares without interval and four squares kept flickering, and a speaker would announce the result right after the recognition was completed. The corresponding functions of each visual stimulus are shown in figure 1d, which means to control the drone to move forward, backward, to the left and to the right for 10 cm respectively.

2.2. Signal Processing

Canonical correlation analysis (CCA) algorithm can obtain the correlation between two sets of multidimensional variables. It seeks a set of linear transformation of them and makes the correlation between them the largest. Filtering EEG signal in a set of band-pass filters before calculating CCA result, is called filter bank canonical correlation analysis (FBCCA) [7]. Extended-FBCCA algorithm mixed SSVEP data of each frequency into the sines and cosines reference signals of each frequency as the reference template, which further improves the recognition accuracy of FBCCA.

When multiple sets of EEG signals are recorded while performing the same task several times, and the most stable and consistent components among EEG signals should be considered task-related. Based on this concept, a task correlation component analysis algorithm (TRCA) was proposed [8], which obtained the most relevant components of the task through linear transformation of the original signal. In screen-based SSVEP, TRCA has a better performance while in AR-SSVEP extended-FBCCA has a better performance [9]. So, we used TRCA in experiment 1 and extended-FBCCA in experiment 2.

In the previous work, extended-FBCCA and its relevant methods were used to match the EEG data with the same template. Which meant whatever the phase of the EEG data was, they would be calculated with the same template. However, phase plays a very important role in model matching. Simply matching the data with the template which probably has a different phase might do harm to the accuracy. In this work, we proposed an idea of matching the EEG data with the template of the same phase.

The continuous flickering SSVEP recognition process is shown in figure 2. In this work, a phase matching method between test data and template was proposed. In order to know the phase, visual stimulation device sent the time synchronization information to the EEG amplifier at the beginning of the experiment. Then at any given time \( t \), given data length \( T \), the phase \( \phi(f(t)) \) of the stimulus would be available (\( f \) is the frequency), because stimuli flicker continuously and the initial phases were known. However, due to the visual pathway, there would be a latency 140 ms after the subject focused on a
visual stimulus for SSVEP signals to appear. In this way, the phase of test data should be $\varphi_{f(t)} + \text{the corresponding phase of } 140\text{ms}$. The EEG data with the same phase with the test data were intercepted from the training model and were used as templates. EEG data with the same phase and length of all frequencies were extracted to do classification. And in this way, every time $T$ there will be an output, instead of the time $T$ plus stimulus interval. In this work, we output a result every 0.3 s.

**Figure 2.** Recognition process of continuous flickering SSVEP.

### 2.3. High Tolerance Criterion

If a subject’s attention is diverted from target A to target B, and the recognition result of that trial (contain target shifting) is A or B instead of other categories, we count this recognition as right. We define this as the high tolerance criterion.

### 3. Result

#### 3.1. Experiment 1

The recognition results of the five subjects in the screen-based continuous SSVEP feasibility verification experiment are shown in figure 3 and table 1. The vertical coordinate of figure 3 represents the categories of 8 different stimuli. As can be seen from figure 3 and table 1, when continuous recognition was performed every 300 ms, most of the recognition results were consistent with the target of the subject’s gaze, and the average recognition accuracy reached 85.3%. In particular, when the subject’s attention is not diverted, continuous flickering SSVEP can better identify the target of subject’s gaze, and the average recognition accuracy without attention shifting is 92.7%. However, in the case of target change, it is easy for system to make recognition errors in attention shift period, and the recognition accuracy rate of the period of attention shift under the condition of high tolerance is 75.2%. Under the condition of high tolerance, the recognition accuracy of all the trials reached 90%, and the continuous recognition system could still reflect the intentions of the subjects effectively.

The average offline ITR of the five subjects was 400.5 bit/min. Note that the ITRs here were virtual ITRs. Virtual ITR means ITR was calculated by the data length $T$ and corresponding time used in classification, instead of the time the stimuli flickered [10]. In other work, the highest offline ITR was 353.3 bit/min [11]. The continuous flickering SSVEP proposed in this study improved the ITR of SSVEP-BCI system because it usually took about 800 ms for high-performance SSVEP-BCI system to output a result, while in this work it was 300 ms. Continuous flickering SSVEP system can greatly shorten the instruction output time and increase the number of correct instructions per minute.
Table 1. Recognition accuracy of 5 subjects in experiment 1.

| Subject | All Period | Without Attention Shift | Attention Shift Period -High Tolerance | All period -High Tolerance |
|---------|------------|-------------------------|---------------------------------------|---------------------------|
| 1       | 0.851      | 0.921                   | 0.675                                 | 0.879                     |
| 2       | 0.883      | 0.974                   | 0.800                                 | 0.945                     |
| 3       | 0.877      | 0.964                   | 0.779                                 | 0.937                     |
| 4       | 0.912      | 0.969                   | 0.870                                 | 0.957                     |
| 5       | 0.741      | 0.808                   | 0.636                                 | 0.780                     |
| Average | 0.853      | 0.927                   | 0.725                                 | 0.900                     |

3.2. Experiment 2

The results of experiment of drone controlled by AR-BCI system through continuous stimulus SSVEP are shown in figure 4. The vertical coordinate of figure 4 represents the categories of 4 different stimuli. The recognition accuracy, ITR and average output of correct instructions per minute of continuous and interval flickering SSVEP are shown in table 2. As can be seen from figure 4 and table 2, in the AR-BCI system, the continuous recognition method can still effectively identify the target of the subject’s gaze, with an average recognition accuracy of 90%, and the recognition errors mainly occur in the period of attention shift. In the AR-BCI control drone experiment, interval flickering SSVEP achieved an average recognition accuracy of 93.5%, which was higher than that of continuous flickering SSVEP. The low accuracy in attention shifting period during the recognition process in continuous flickering SSVEP lowered the overall average recognition accuracy. In terms of speed, the output time of continuous flickering SSVEP for each instruction is 2s, while the output time of interval flickering SSVEP is 3s, so the output time of continuous flickering SSVEP is greatly reduced. The large increase in speed compensated for the small decrease in accuracy. And overall, the continuous flickering SSVEP achieved an average ITR of 49.1 bit/min. It is an improvement compared with the present results in other work.
Figure 4. Recognition results of 5 subjects in drone experiment controlled by AR-BCI system through continuous stimulus SSVEP.

Table 2. Results in experiment 2.

| Subject | Accuracy | ITR (bit/min) | Correct Order Output Per Min |
|---------|----------|---------------|-------------------------------|
|         | Continuous a | Interval b | Continuous | Interval | Continuous | Interval |
| 1       | 0.900     | 0.975        | 41.2        | 35.8     | 27         | 19       |
| 2       | 0.975     | 1.000        | 53.8        | 60.0     | 29.25      | 20       |
| 3       | 0.825     | 1.000        | 31.6        | 60.0     | 24.75      | 20       |
| 4       | 0.800     | 0.725        | 28.8        | 14.3     | 24         | 14.5     |
| 5       | 1.000     | 0.975        | 90.0        | 35.8     | 30         | 19.5     |
| Average | 0.900     | 0.935        | 49.1        | 41.2     | 27         | 18.7     |

a Stimuli were continuous; b Stimuli flickered with interval.

4. Conclusion
Continuous flickering SSVEP can better adapt to the process control BCI and improve the ITR of the system. This work achieved continuous flickering SSVEP system, verified the feasibility of continuous flickering SSVEP method in screen-based BCI system, and realized the application of AR-BCI control drone. In AR-BCI system, continuous flickering SSVEP-BCI system performed better than that with intervals in the ITR and the number of correct instructions output per minute. In this work, performance of AR-BCI was improved, and we provided a new idea for high-speed AR-BCI SSVEP system.

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References
[1] Wolpaw J R, Birbaumer N and Heetderks W J 2000 Brain-computer interface technology: A review of the first international meeting IEEE Transactions on Rehabilitation Engineering 8 164-73.
[2] Krucoff M O and Rahimpour S 2016 Slutzky MW Enhancing nervous system recovery through neurobiologics, neural interface training, and neurorehabilitation Frontiers in Neuroscience 10 584.
[3] Sellers E W and Donchin E 2006 A P300-based brain-computer interface: Initial tests by ALS patients Clinical Neurophysiology 117 538-548.
[4] Wang M, Li R and Zhang R 2018 A wearable SSVEP-based BCI system for quadcopter control using head-mounted device *IEEE Access* **6** 26789-26798.

[5] Zhang L, Wu X and Guo X 2019 Design and implementation of an asynchronous BCI system with alpha rhythm and SSVEP *IEEE Access* **7** 146123-146143.

[6] Kalunga E K, Chevallier S and Barthélemy Q 2016 Online SSVEP-based BCI using Riemannian geometry *Neurocomputing* **191** 55-68.

[7] Chen X, Wang Y, Gao S, Jung T P and Gao X 2015 Filter bank canonical correlation analysis for implementing a high-speed SSVEP-based brain-computer interface *Neural. Eng.* **12** 4.

[8] Nakanishi M, Wang Y and Chen X 2018 Enhancing detection of SSVEPs for a highspeed brain speller using task-related component analysis *IEEE Transactions on Biomedical Engineering* **65** 104-12.

[9] Yufeng K, Pengxiao L, Xingwei A, Xizi S and Dong M 2020 An online SSVEP-BCI system in an optical see through augmented reality environment *Journal of Neural Engineering* **17** 1.

[10] Sengelmann M, Engel A K and Maye A 2017 Maximizing information transfer in SSVEP-based brain-computer interfaces *Biomedical Engineering IEEE Transactions on Biomedical Engineering* **64** 381-394.

[11] Jiang J, Yin E and Wang C 2018 Incorporation of dynamic stopping strategy into the high-speed SSVEP-based BCIs *Journal of neural engineering* **15** 046025.