VR-SSVEPeripheral: Designing Virtual Reality Friendly SSVEP Stimuli using Peripheral Vision Area for Immersive and Comfortable Experience

Jinwook Kim
jinwook.kim31@kaist.ac.kr
Korea Advanced Institute of Science and Technology
Daejeon, South Korea

Taesu Kim
tskind77@kaist.ac.kr
Korea Advanced Institute of Science and Technology
Daejeon, South Korea

Jeongmi Lee
jeongmi@kaist.ac.kr
Korea Advanced Institute of Science and Technology
Daejeon, South Korea

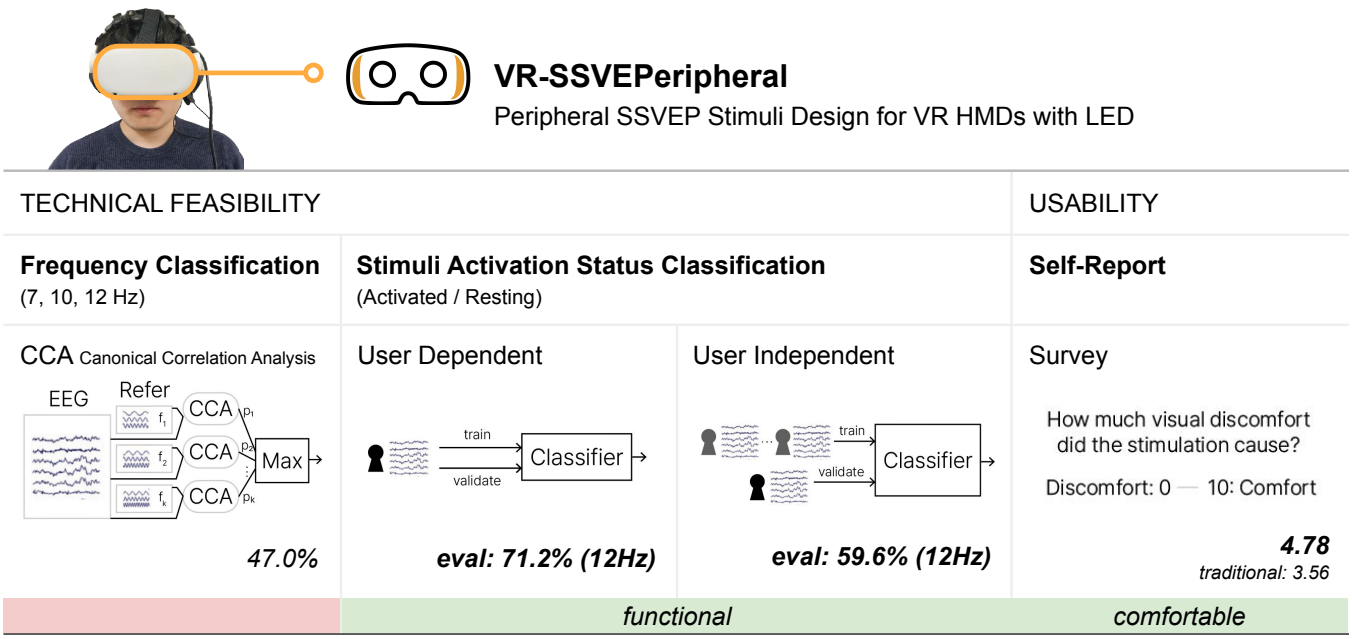

Figure 1: The overview of the offline experiment for functionality and usability verification. We conducted an experiment to collect EEG data when viewing SSVEP stimuli and analyzed it in two ways: target frequency and stimuli activation status classification. We also used a survey regarding visual comfort. The result indicates that VR-SSVEPeripheral was more comfortable than the previous stimuli (Central) and functional for augmenting synchronized brain signals for SSVEP detection.

ABSTRACT

Recent VR HMDs embed various bio-sensors (e.g., EEG, eye-tracker) to expand the interaction space. Steady-state visual evoked potential (SSVEP) is one of the most utilized methods in BCI, and recent studies are attempting to design novel VR interactions with it. However, most of them suffer from usability issues, as SSVEP uses flickering stimuli to detect target brain signals that could cause eye fatigue. Also, conventional SSVEP stimuli are not tailored to VR, taking the same form as in a 2D environment. Thus, we propose VR-friendly SSVEP stimuli that utilize the peripheral, instead of the central, vision area in HMD. We conducted an offline experiment to verify our design (n=20). The results indicated that VR-SSVEPeripheral was more comfortable than the conventional one (Central) and functional for augmenting synchronized brain signals for SSVEP detection. This study provides a foundation for designing a VR-suitable SSVEP system and guidelines for utilizing it.

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CCS CONCEPTS

• **Human-centered computing** → **User studies**; **Virtual reality**;
• **Hardware** → **Emerging interfaces**.

KEYWORDS

Virtual Reality, Brain-Computer Interface, Steady State Visually Evoked Potentials (SSVEP), Electroencephalography (EEG), Usability, Immersion

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1 INTRODUCTION

Recent virtual reality head-mounted displays (VR HMDs) are trying to embed EEG to receive brain signals for evaluating user status in VR or developing novel Brain-Computer Interface (BCI) based VR interactions [5, 17, 36]. Among these approaches, Steady-State Visual Evoked Potential (SSVEP) is the most widely used BCI method in a 2D environment for manipulating interfaces such as button selection and text typing [2, 11, 29, 38]. SSVEP is a method of detecting specific brain wave patterns in the occipital lobe when a user gazes at a visual stimulus that blinks at a certain frequency [6, 13, 40]. Brain signals are acquired with the EEG device and segmented into specific time windows (250 to 1000ms). From the segmented data, the features are extracted using functions such as Short-time Fourier Transform analysis and Power Spectral Density (PSD) [8, 48]. These features are used to conduct Canonical Correlation Analysis (CCA) or more advanced algorithms, such as Convolutional or Recurrent Neural Network (CNN/RNN), to classify or detect which frequency the user is currently viewing [2, 13, 28]. These advanced machine learning algorithms have significantly improved brain signal detection speed and accuracy [15, 25, 28].

In contrast to the progress of technical development, the approach from a usability perspective is still insufficient [34, 42]. Moreover, these BCI methods are applied to VR interaction systems without being tailored to the VR HMD environment [7, 23]. Existing BCI systems mainly use a method of augmenting brain signals with flickering stimuli such as SSVEP and P3 Speller, and the current form that is used in a 2D environment is currently applied as is to content in VR [7, 21, 42]. Novel VR interactions based on BCI can provide users with new experiences, but flickering stimuli could interfere with content immersion and cause eye fatigue in long-term use. Thus, different approaches are needed from both technical and usability perspectives to improve its usability for VR usage [32].

In this paper, we propose SSVEP stimuli designed for the peripheral vision area. This approach addresses a limitation of VR—the restricted field of view—within the context of VR head-mounted displays (HMDs) [30, 46]. Through our design, we aim to maintain the technical performances while minimizing the visual discomfort of SSVEP stimuli. We conducted an offline experiment to verify the technical feasibility and evaluate the usability of our SSVEP stimuli design. The result showed that VR-SSVEPeripheral was functional and more comfortable than the previous stimuli for augmenting synchronized brain signals for SSVEP detection. Based on the result, we propose that our research makes the following contributions:

- We utilized the peripheral vision area to design VR-friendly SSVEP stimuli and verified the technical feasibility and visual comfort improvement through the offline experiment.
- This paper is the first to design comfortable SSVEP stimuli for VR. Previous studies have evaluated the stimuli size or contrast [42], but none have attempted to design novel stimuli forms.
- Based on the result, we revealed relative strengths and weaknesses by comparing it with the traditional SSVEP stimuli (Central) and propose design guidelines for using SSVEP for VR interaction using both central and peripheral methods. Thus, this study contributes to BCI for VR and expands the interaction space.

2 RELATED WORK

BCI has been mainly used for typing, wheelchair, and robot remote commands to assist people with limited mobility or medical purposes [1, 53]. This was due to the high cost of EEG, the inconvenience of wearing the device, and low Signal-to-Noise Ratio issues. However, in recent years, EEG devices have become a more comfortable form to measure brain signals with dry electrode [9, 24], and many methods have been developed to find meaningful signals even when there is a lot of noise [3, 15, 50]. With this improvement, many attempts have been made to utilize BCI for daily life such as games or Internet of Things (IoT) other than specialized purposes. For instance, various commercial EEG products such as Nextmind and Looxid Labs can be used to change TV channels or manipulate 2D/3D game interfaces, and remotely control IoT devices on AR devices [7, 18, 23, 24].

However, in this transitional phase, many BCI studies still lack consideration of the usability of these systems [2, 16]. They mostly focus on developing various machine learning or algorithms to improve classification accuracy or detection speed [14, 20]. On the other hand, in recent years, there have been some studies that have tried to improve the usability and accessibility of the BCI system. For instance, to reduce the discomfort caused by SSVEP stimuli with flickering lights, alternative approaches such as rotating patterns and icons are suggested [12, 40]. Other studies have also compared accuracy and user preference depending on stimulus size, illuminance, and frequency rate in VR [42], but no studies have yet attempted to design novel stimuli forms for VR.

In the future, a user experience-related approach will be more important for BCI to be applied for general usage, especially in VR [11, 31]. The most challenging part of this VR approach is creating visually comfortable stimuli for the user and contextualizing them in a virtual reality environment while maintaining the performance of the BCI system (e.g., accuracy, classification time, etc) [26]. In 2D environments, visual comfort was the only feature that needed to be considered, but in VR environments, it is important to develop stimuli that do not break the sense of immersion since users frequently interact with multiple virtual objects beyond a simple UI. Therefore, we propose SSVEP stimuli by utilizing the peripheral vision area to improve the current BCI system for VR interaction.

3 VR-SSVEPeripheral DESIGN

We aimed to design VR SSVEP stimuli that are both comfortable and functional in this study. Thus, we gained some insights from the previous work that utilized peripheral vision areas in VR and 2D environments [19, 26, 46, 52]. First, Xiao and Benko proposed SparseLightVR, which provides ambient light around the HMD

lenses to extend the VR contents and nearly fill the human field of view (FoV) [46]. Through the user test, they verified that Sparse-LightVR has successfully expanded FoV up to 190°and enhanced situational awareness. On the other hand, in terms of utilizing the peripheral field for SSVEP stimuli in a 2D environment, Lee et al. conducted a study comparing mental fatigue between central and peripheral SSVEP stimuli [26]. They designed circular stimuli and divided the central and peripheral into inner and outer circles. The results of their study indicate some trade-off effects on detection accuracy when peripheral SSVEP stimuli were used for visual comfort. However, it still has a significant effect on decreasing visual fatigue. Overall, these studies propose possibilities that peripheral areas in VR HMD could contribute to solving various issues in both VR and BCI fields.

Inspired by the previous approaches, we designed peripheral SSVEP stimuli in the VR HMD supported by LEDs. Since various research reported a trade-off effect between usability and feasibility when the stimuli are presented in the peripheral area, we used LED to augment more powerful synchronized brain signal [44, 45]. As shown in Figure 2, two LED strips (SK6812-RGB-NW) were attached around the lenses and faced the outer side of HMD to use light reflection for interference and glare reduction. A total of 20 LED chips, ten each on the outer side area, were used to implement our design. When the LED inside of HMD was illuminated, the light intensity measured at eye level was 5,300K, 147 lx.

In addition, only a single SSVEP stimulus can be presented at a time in this form. In the 2D environment, providing multiple stimuli on the screen is essential due to the lack of a targeting method instead of a mouse cursor. However, in recent VR HMDs, various targeting methods (i.e., eye and head tracking) are available to assist users' selection. Along with these targeting methods, our approach could widen the range of design space for VR interaction and promote BCI usage.

Figure 2: An image of VR-SSVEPeripheral activated on Meta Quest 2 VR HMD. The position of the activated LED strip is highlighted.

4 EXPERIMENT

To evaluate and verify our SSVEP design, we conducted an offline experiment that could collect EEG data while viewing each stimulus in various frequencies (7, 10, and 12 Hz) [40, 42]. We also included traditional SSVEP stimuli, which present the stimuli on the central vision area, to compare the usability and verify methods used for analysis. The target (Sphere, size: 9.5°, Distance: 6 m) was provided during the trial, and participants were asked to focus on the sphere. The sphere flickered at a specific frequency in the central SSVEP presentation stimuli (Central) condition. On the other hand, the LED placed on the VR HMD peripheral area (Peripheral) is triggered to flicker in our peripheral SSVEP stimuli condition.

The experiment was performed using Meta Quest 2 (3664 x 1920 resolution, 90 Hz refresh rate, 100°FoV). For brain signal acquisition, we used a dry-type 32-channel EEG device (CGX Quick-32r). In this experiment, we utilized only six channels placed on the occipital lobe (O1, O2, Oz, P3, Pz, P4) with a sampling frequency of 500 Hz. The experiment was performed using Unity 3D to implement a VR experiment environment on AMD Ryzan 9 5900X, 32GB RAM, and an NVIDIA RTX 3090 desktop. Serial communication was used to send a signal from Unity to trigger peripheral stimuli built with LED strips wired to Arduino Nano.

4.1 Participants

We recruited 20 participants from the university, but due to poor EEG calibration, two subjects failed to accomplish the full task and were excluded. Among the 18 participants who completed the full task (Mean age=26.61, SD=3.78, 13 Male), all participants had previous experience using VR, but none had experience using SSVEP. All of the study protocols and methods were approved by an Institutional Review Board (IRB) of the university, and participants were rewarded $20 for participating in the experiment.

4.2 Procedure

The experimenter first explained the task and the experimental procedure. Then, participants conducted a survey about previous VR and SSVEP experiences. After the survey, participants wore an EEG device, and the experimenter adjusted the electrode to lower the impedance below 600 kΩ to receive clean brain signal data. After adjustment, they wore VR HMD as Figure 1 and proceeded to the task. The trial blocks for each SSVEP presentation method were presented in a counterbalanced order, and flickering frequency (7, 10, 12 Hz) was presented in randomized order. The experiment contained 180 trials, 90 trials for each stimuli presentation method, and a rest phase was provided after every 45 trials. In each trial, participants were asked to focus on the target for four seconds and relax when the target was changed to cross for five seconds (see Figure 3). After each block, participants were asked to fill out the survey about visual comfort in a 10-point Likert scale [42]. The entire experimental session took about 50 minutes to complete on average.

5 RESULTS

During the experiment, brain signals, event logs, and survey responses were collected. In terms of brain signals, a high and low pass filter was applied to get signals between 0.1 and 60 Hz. Then, the data was segmented into trial units based on the event markers. After preprocessing, it was classified into two ways: target frequency and activation status. Previous studies only conducted target frequency classification, classifying the frequency the user

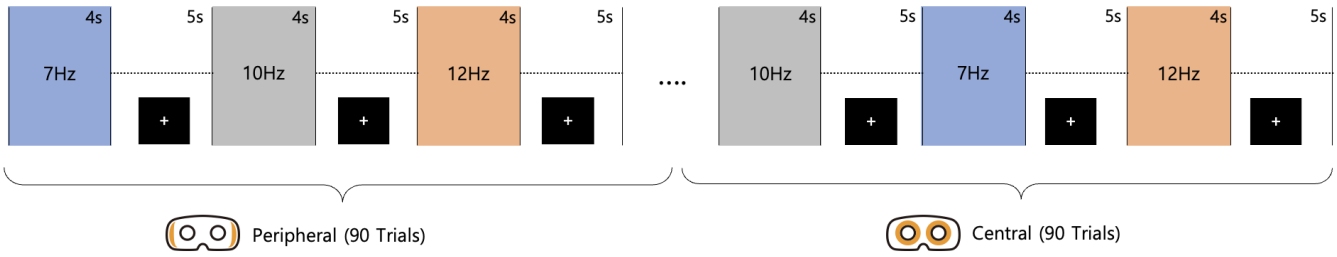

Figure 3: The illustration of the experiment trial procedure. The SSVEP display method (Central and Peripheral) was presented in a counterbalanced order, and target frequency (7, 10, and 12 Hz) was provided in random order in each block. A sphere was presented as a target object during the trial state (4s), and it was changed to the fixation point (cross) in the resting state (5s) to indicate the target location.

focused on [40, 42]. However, due to the form of our design, which can not present multiple flickering frequencies simultaneously, the classification of whether SSVEP stimuli are activated and focused is required. Thus, we conducted both classifications to explore the pros and cons of each method and to provide design guidelines for utilizing SSVEP in VR applications. The detailed analysis methods and results are as follows.

5.1 Target Flickering Frequency Classification

First, we conducted a Canonical Correlation Analysis (CCA) to classify which target frequency stimuli the user was focusing on during each trial. CCA is a commonly used algorithm in the SSVEP-based BCI method due to its high classification performance and does not require a pre-training phase [10, 27, 35]. It computes the linear transformations of EEG data with each template signal (Fourier series) and recognizes the target frequency by maximizing the correlation (see Figure 1 CCA section). For instance, when the user focuses on the 7 Hz SSVEP stimuli, the synchronized brain signal is generated at the multiples of the target frequency (i.e., 7, 14, 21 Hz). The CCA algorithm computes the correlation between the brain signal input and each target frequency template and classifies it based on the maximum correlation value.

The study utilized three template signals (7, 10, and 12 Hz) on segmented EEG data. Additionally, we examined classification accuracy across various time window lengths, ranging from 0.25s to 2s in 0.05s increments. The CCA was performed using a sliding window technique (25% overlap) on each trial data (4s), and the overall results are presented in Figure 4.

The results indicate that traditional SSVEP stimuli, displaying stimuli on the target object directly, show high accuracy (> 75%) from the 0.75s time window as the previous studies [33]. However, the classification accuracy of peripheral SSVEP stimuli was lower than 50% in all time window lengths. This could be due to the trade-off effect of displaying the stimuli in the peripheral vision area rather than directly displaying them in the center [26].

5.2 Stimuli Activation Status Classification

Since peripheral SSVEP stimuli can only present one frequency at a time, we conducted a classification between the resting state and stimuli-activated/focused state. Among the resting state EEG data between each trial (5s), the first second was discarded and the remaining (4s) was utilized in this analysis. Each data was segmented into two-second lengths, resulting in 120 data samples (60 activated, 60 resting) for each presentation and frequency condition. Lastly, the data was normalized, and Welch Power Spectral Density (PSD) was applied to extract the signal power of each frequency band [8, 48].

In addition to user-dependent (Intra-subject) evaluation, we evaluated independent (Inter-subject) cases to explore the generalization and possibility of training-free usage [39, 47]. For user-dependent conditions, we divided individual data into test and validation sets at an 8:2 ratio and performed classification on each participant's data (5-fold cross-validation). In user-independent conditions, 17 participants' data was used for training, and one participant was used for model evaluation (18-fold cross-validation). Overall Support Vector Machine (SVM) was used to conduct classification [49] and the cross-validation results are described in Table 1.

From the result, we found that overall user-dependent cases show high classification accuracy in both central and peripheral stimuli presentation (> 70% evaluation accuracy in 12 Hz). In addition, the result showed that the evaluation accuracy increases at a higher target frequency in peripheral presentation conditions. This result indicates that peripheral SSVEP stimuli could be utilized for VR triggering or selection methods. On the other hand, in the user-independent case, classification performance was not promising to verify the generalization and train-free usage. This could be due to the high influence of individual differences of EEG data [37] and BCI illiteracy [4].

5.3 Visual Comfort

In order to evaluate the stimuli design, a survey regarding visual comfort was collected after experiencing each SSVEP presentation method. The survey question was 'How much visual discomfort did the stimulation cause?' and the answer was collected with 1 being discomfort and 10 being comfortable [42]. The responses were analyzed with the Wilcoxon signed-rank test. As Figure 4, the result (p=.008, Z=-2.632) showed that our peripheral SSVEP stimuli design (M=4.78, SD=2.10) was more comfortable than traditional stimuli (M=3.56, SD=1.65).

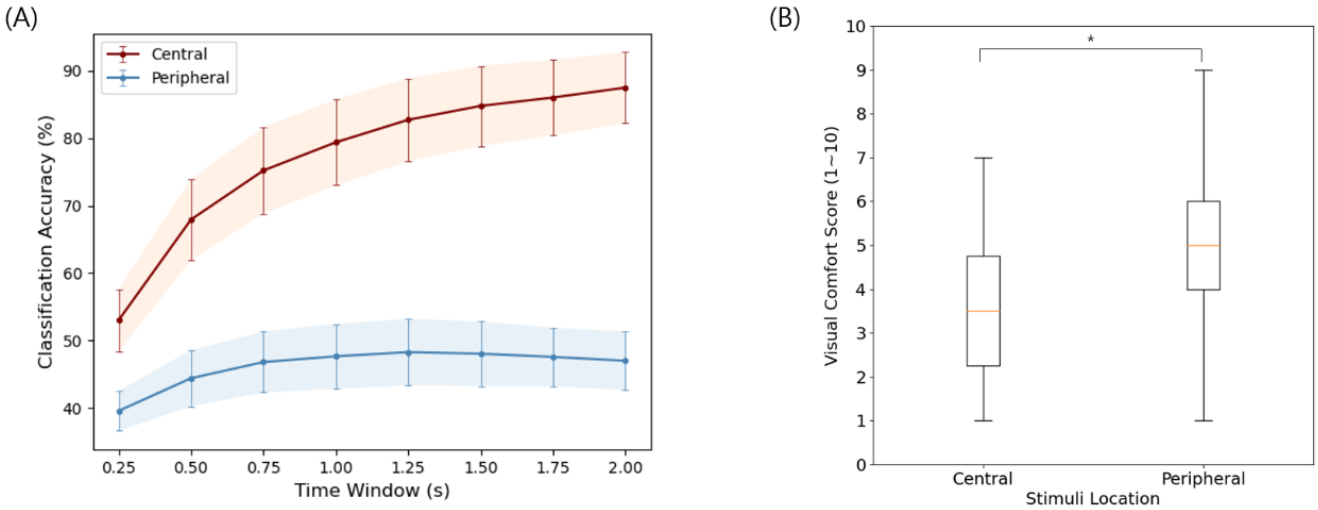

Figure 4: The result of target flickering frequency classification and survey. (A) The average accuracy of CCA results for each time window (second) length. The error bars represent the 95% confidence intervals. (B) The boxplot illustrating the result of the SSVEP stimuli comfortableness survey on a 10-point Likert scale (1=discomfort, 10=Comfortable; *=p<0.01).

		User Dependent		User Independent	
Presentation Type	**Hz**	**Train Acc**	**Eval Acc**	**Train Acc**	**Eval Acc**
Central	7	0.920 (0.010)	0.760 (0.053)	0.828 (0.005)	0.695 (0.088)
Peripheral	7	0.886 (0.141)	0.679 (0.054)	0.739 (0.005)	0.584 (0.089)
Central	10	0.919 (0.104)	0.744 (0.050)	0.807 (0.006)	0.660 (0.089)
Peripheral	10	0.892 (0.142)	0.697 (0.067)	0.760 (0.005)	0.588 (0.083)
Central	12	0.910 (0.139)	**0.772 (0.064)**	0.809 (0.007)	0.685 (0.094)
Peripheral	12	0.907 (0.144)	**0.712 (0.054)**	0.766 (0.005)	0.596 (0.104)
Central	All	0.893 (0.111)	0.779 (0.058)	0.795 (0.004)	0.675 (0.089)
Peripheral	All	0.866 (0.139)	0.717 (0.067)	0.739 (0.005)	0.597 (0.098)
Central Average		0.910 (0.012)	0.764 (0.015)	0.810 (0.013)	0.679 (0.015)
Peripheral Average		0.888 (0.017)	0.701 (0.017)	0.751 (0.014)	0.591 (0.006)

Table 1: The average classification accuracy of stimuli activation status based on SVM. We analyzed the performance by dividing the dataset into presentation type, target frequency, user-dependent, and independent case. Along with the average of each case, the standard deviation is reported in the parenthesis.

6 DISCUSSION & CONCLUSION

In this paper, we propose VR-SSVEPeripheral, VR-friendly SSVEP stimuli that utilize peripheral vision areas in VR HMDs. We conducted an offline experiment to technically verify our design and evaluate its usability. From the result, we found that displaying SSVEP in the peripheral vision area was more comfortable for users. In terms of classification performance, the traditional SSVEP method showed promising results for both target frequency and stimulus state classification as the previous studies [11]. However, there was some trade-off effect between comfort and band power at the target frequencies [26] in the peripheral presentation method condition. Specifically, the frequency classification (CCA) results showed less than 50% performance when the stimuli were presented peripherally, but the result of the stimuli activation status classification (SVM) task showed promising results (> 70%).

Thus, these results reveal that presenting SSVEP stimuli in the peripheral vision area is inappropriate for using multiple frequencies. Still, it is possible to detect when a stimulus is present and focused. This result may be fatal in 2D environments where users interact with multiple interfaces (e.g., buttons, word inputs). However, in a VR environment, where there are additional targeting methods (i.e., eye, head, and hand), SSVEP can open up a new VR interaction space when used as a triggering method. For instance, if eye-tracking and EEG are used as a targeting/triggering method in a teleportation method when exploring a virtual world or remote space, it will facilitate users' multitasking by relieving the burden

of tasks and functions concentrated on the hands [21, 22, 41]. Given a single target (i.e., teleportation, push buttons, shooting), a peripheral presentation form of SSVEP can be used to design a relatively comfortable and immersive interaction experience.

We have analyzed basic algorithms such as CCA and SVM to validate the new method. Therefore, we expect that several approaches can be taken to improve the classification performance. First, it could be improved by using more advanced algorithms and machine learning models proposed in recent studies (e.g., CNN, RNN, Filter Bank) [28, 43, 51]. In addition, we found that stimuli activation classification performance was improved in higher target frequency in the peripheral SSVEP stimulus condition. Previous studies have shown that when presenting stimuli with LEDs, unlike screen bases, higher frequencies can be employed without a maximum frequency limit [53]. It would be possible that presenting stimuli with higher flickering frequencies could lead to improved performance and less intrusive stimuli. Finally, the use of EEG data augmentation [28], which has recently been proposed as an advance in generative AI, could improve overall performance, especially in user-independent cases.

Therefore, future work should first attempt to improve the classification performance. Then, a more comprehensive user experience that measures immersion, comfort, and online SSVEP detection performance should be evaluated by adopting these SSVEP methods for VR interaction (i.e., locomotion, UI selection, and multitasking). In addition, exploring the interaction effect between VR content and peripheral SSVEP stimuli could help improve immersion. For example, it might be possible to try presenting different light intensities or colors of LEDs in conjunction with the context of the VR content. Based on these improvements, we expect to be able to present practical design guidelines for utilizing BCI methods for VR interaction.

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