# Brain-Controlled, AR-Based Home Automation System Using SSVEP-Based Brain-Computer Interface and EOG-Based Eye Tracker: A Feasibility Study for the Elderly End User

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***Abstract*—Over the past decades, brain-computer interfaces (BCIs) have been developed to provide individuals with an alternative communication channel toward external environment. Although the primary target users of BCI technologies include the disabled or the elderly, most newly developed BCI applications have been tested with young, healthy people. In the present study, we developed an online home appliance control system using a steady-state visual evoked potential (SSVEP)-based BCI with visual stimulation presented in an augmented reality (AR) environment and electrooculogram (EOG)-based eye tracker. The performance and usability of the system were evaluated for individuals aged over 65. The participants turned on the AR-based home automation system using an eye-blink-based switch, and selected devices to control with three different methods depending on the user's preference. In the online experiment, all 13 participants successfully completed the designated tasks to control five home appliances using the proposed system, and the system usability scale exceeded 70. Furthermore, the BCI performance of the proposed online home appliance control system surpassed the best results of previously reported BCI systems for the elderly.**

***Index Terms*—Augmented reality, brain-computer interface, electroencephalography, electrooculography, steady-state visual evoked potential.**

## I. Introduction

BRAIN-COMPUTER interface (BCI) technology facilitates communication between users and external environments without involving any physical body movements [1], [2]. Various non-invasive techniques have been employed to measure brain activity, including magnetoencephalography (MEG), functional near-infrared spectroscopy (fNIRS), and electroencephalography (EEG). Among these, EEG has been most widely used owing to its affordability, portability, and ease of use. Over the past decades, various EEG-based BCIs have been developed and used in a range of applications, such as games [3], communication applications [4], [5], wheelchair control [6], and smart home automation [7], [8].

Although the target users of BCI systems primarily comprise the elderly and people with physical disabilities, most BCI systems developed to date have been tested with the healthy, young population [9]. There are several reasons why BCI systems have not been applied to target users. First, most BCI studies are conducted in universities where participants in their twenties are readily available. Second, it is difficult to recruit elderly subjects or patients compared to healthy young subjects [10], [11].

The participation of young, healthy subjects may lead to the overestimation of the performance of a developed BCI system. Consequently, the "true performance" of the system may remain unknown. In previous studies, it has been frequently reported that compared to the older population, the participation of the younger population exhibited significantly higher BCI performance, particularly in terms of classification accuracy. For instance, Chen et al. [12] reported their vibro-tactile BCI system showed lower classification accuracy for an older population, compared to a younger population. Moreover, Gembler et al. [9] also reported that a group of elderly participants exhibited lower classification accuracy than a group of young participants in a BCI speller application based on steady-state visual evoked potential (SSVEP)-based BCI. Furthermore, in a study that investigated the variations of performance in sensorimotor-rhythm (SMR)-based BCIs, the authors stated that a negative correlation between age and BCI performance was conceivable [13]. Similarly, a succession of studies has reported evoked potentials with higher amplitude and shorter latency in younger participants than in older participants [14], [15], [16], which most likely resulted in higher performance of BCI systems based on evoked potentials.

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In the present study, we developed a home automation (HA) system by combining SSVEP-based BCI, augmented reality (AR), electrooculogram (EOG)-based eye tracker, and internet-of-things (IoT) technologies. Subsequently, we evaluated the performance and usability of the system for people aged over 65 years. Accordingly, the participants were asked to control home appliances through the SSVEP-based BCI, an eyeblink-based asynchronous switch, and an EOG-based eye-tracker, without any external assistance. During the experiment, all the user interfaces were presented in an AR environment via a commercially available head-mounted display (HMD). Depending on whether a device was compatible with IoT, the home appliances were controlled either wirelessly in an IoT-based network or using infrared (IR) signals. The performance of the proposed system was evaluated in online experiments involving participants aged over 65 years, where five types of home appliances were controlled in real-time. Furthermore, the usability of the proposed system was also assessed with a questionnaire called system usability scale (SUS) that has been widely employed to quantitatively evaluate the practical usability of a system [17].

This study is sectioned as follows: The methods used in the offline experiments to determine the optimal visual stimulation time and electrode configurations are described in Section 2A. Detailed descriptions of the proposed home appliance control system and the online experimental paradigms are presented in section 2B. The experimental results from the offline and online experiments are presented in Section 3A and 3B, respectively. Lastly, some issues associated with the proposed system are discussed in Section 4.

## II. Methods

### A. Experiment I – Offline Experiment to Determine Optimal Duration of Visual Stimulation and Individualized Electrode Configuration

*1) Subjects:* In total, 21 healthy individuals aged over 65 years (10 females and 11 males, average age 67.5 ± 3.0 years, ranging between 65 and 75) participated in the offline experiment that aimed to determine optimal window size and individualized electrode configuration. All participants had a normal or corrected-to-normal vision and none of them had a history of neurological, psychiatric, or ocular diseases. The data of two participants were excluded from further analyses because there were no observable spectral peaks at any SSVEP stimulation frequencies in the amplitude spectrum of the recorded EEG data. Therefore, the EEG data of 19 participants were analyzed. Generally, "BCI illiteracy" is a well-known issue in all types of EEG-based BCIs [18].

All participants were informed about the details of the experiments, and gave written consent before the experiment began. The study and the experimental paradigm were approved by the institutional review board of Hanyang University, South Korea (IRB No. HYI-14-167-13).

*2) Experimental Paradigm:* The offline experiment comprised three sessions, each consisting of 25 trials. In each trial, five visual stimuli flickering at 6.6, 7.5, 8.57, 10, and 12 Hz were presented to a see-through display of an AR headset, MS Hololens™ (Microsoft Corp., Redmond, WA, USA).

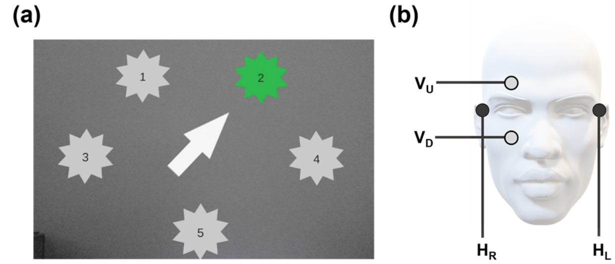


Fig. 1. (a) Visual stimuli presented in Experiment I. The stimulus to gaze in next trial was guided by an arrow. (b) Configuration of four electrodes to compute vertical and horizontal EOG components.

The visual stimuli flickered for 7 s with 7 s inter-stimulus interval (ISI). Meanwhile, the participant was instructed to keep focusing on one of the visual stimuli without blinking and making body movements. In the experiment, we employed a star-shaped stimulus called grow/shrink stimulus (GSS) which flickers and varies its size simultaneously to evoke SSVEP responses, due to its superiority in comparison with the conventional visual stimuli in AR environment in terms of classification accuracy [7]. The visual stimuli for the offline experiment are shown in Fig. 1(a), with the corresponding visual angle set to 6.4°. Note that the visual stimuli were designed to be fixed in designated positions in AR environment to make the users feel more comfortable with the stimuli.

*3) Data Recording and Analysis:* The EEG data were recorded from 12 electrode locations (Cz, Pz, P3, P4, P7, P8, POz, PO3, PO4, Oz, O1, and O2) at a sampling rate of 2,048 Hz from 12 electrode locations using a Biosemi ActiveTwo system (Biosemi, Amsterdam, The Netherlands). Subsequently, the data were down-sampled at a sampling rate of 512 Hz to reduce the computational cost before being bandpass filtered with cutoff frequencies of 2 and 54 Hz to remove low-frequency baseline drift and power line noise (60 Hz) using a Butterworth filter in MATLAB (MathWorks Inc., Natick, MA, USA).

We employed an algorithm called extension of multivariate synchronization index (EMSI) [19] to classify the SSVEP responses. The algorithm recognizes the target frequency by evaluating the synchronization index between given EEG data and reference signal with each stimulation frequency, and then finding the stimulation frequency that maximizes the index. More details on the EMSI algorithm can be found in [19].

To evaluate the feasibility of the proposed system with the universal electrode set, we first computed the classification accuracy with the widely adopted electrodes in SSVEP-based BCIs, O1, Oz, and O2. Subsequently, we calculated the classification accuracies for all possible combinations of three electrodes out of the eleven electrodes attached above the parietal and occipital cortices (Pz, P3, P4, P7, P8, POz, PO3, PO4, Oz, O1, and O2), then selected a set of three electrodes that exhibited the highest performance for each participant.

Moreover, we computed information transfer rate (ITR) [20] with varying window sizes to determine the optimal window size, which was based on the following equation:

$$ITR = \frac{60}{T}\left[\log_2 N + P\log_2 P + (1-P)\log_2\frac{(1-P)}{(N-1)}\right], \quad (1)$$

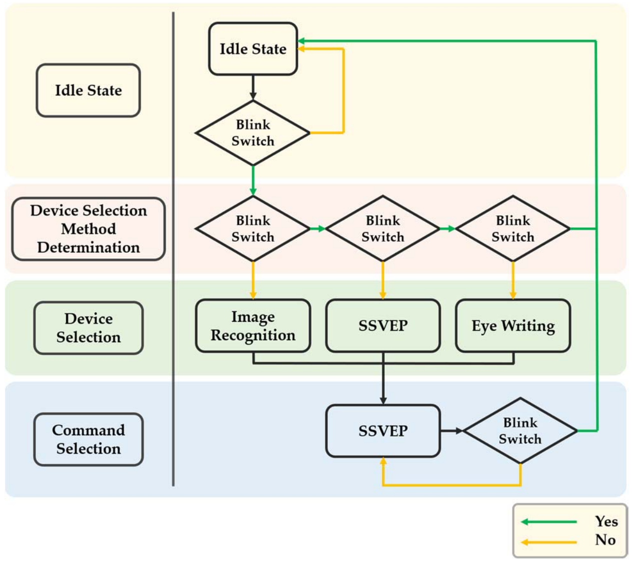


Fig. 2. Flow-chart of the proposed online home appliance control system.

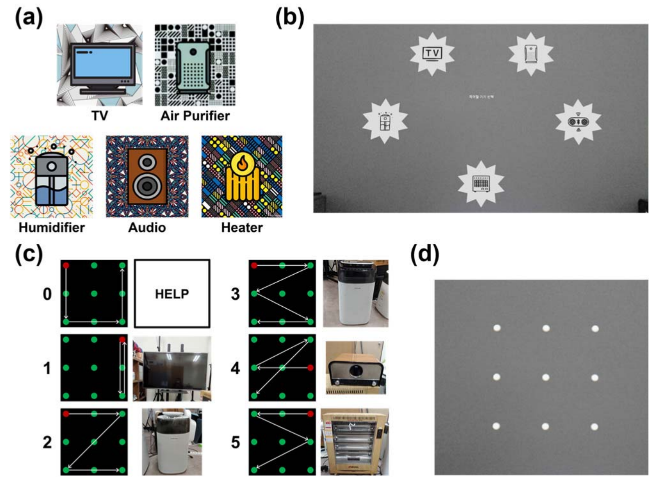


Fig. 3. Three different device selection methods implemented in the online home appliance control system. (a) Image cards corresponding to each device. (b) Five SSVEP stimuli corresponding to each device. Each stimulus flickered at different frequencies and had an icon of the corresponding device. (c) Six eye movement patterns corresponding to each device, and a 'help' command to remind the eye movement patterns. (d) Nine dots presented in the eye writing stage to assist the eye movement.

where $T$ denotes the window size in seconds, $N$ represents the number of possible targets, and $P$ indicates the classification accuracy. Since the testing dataset did not follow a normal distribution (Kolmogorov-Smirnov test), the Bonferroni-corrected Wilcoxon signed rank test was applied to test the statistical significance of the difference between performances for universal and individualized electrode configurations.

### B. Experiment II – Online Home Appliance Control Experiment

*1) Subjects:* We attempted to enroll all participants from the offline experiment for the online experiment as well. Six of nineteen participants refused to participate in the online experiment, primarily due to the prevalence of the COVID-19 pandemic during the online experiment. Consequently, thirteen participants participated in the online experiment.

*2) Data Recording:* The EEG data were recorded from the three electrode locations that were individually determined in the offline experiment. The recording device and sampling rate was the same with offline experiment. Additionally, the EOG signals for eye-tracking were measured from four electrodes attached around the eyes as shown in Fig. 1(b).

*3) Hierarchical Constitution of the Proposed System:* As illustrated in Fig. 2, the proposed system was designed to have multiple stages comprising the following four stages:

(i) *Idle state.* To allow the participants to switch on/off the proposed HA system on their own, an asynchronous switch based on eye blink was employed using multiple-window summation of first derivatives in a sliding window (MSDW) [21]. The MSDW algorithm computes a vertical EOG component to detect an eyeblink by

$$EOG_V = V_U - V_D, \tag{2}$$

where $V_U$ and $V_D$ correspond to the potential values recorded above and below the right eye, respectively, as shown in Fig. 1(b). Accordingly, the system was turned on or off each time four successive eyeblinks were detected within 3 s. Unless the user turns on the switch by successively blinking the eyes, the system remained in an idle state. The user could also turn off the system by using the eyeblink switch and return to the idle state at any time during the system operation.

(ii) *Determination of device selection methods.* The proposed HA system provided three options that the user can take to select a device to control (image recognition, SSVEP, and eye writing). Accordingly, the user could select the device using a method they prefer. Once a user turned on the system via the eyeblink switch, the user could select the target device to control using one of the three methods. The control method was determined based on the number of executions of the eyeblink switch. Image Reconstruction method was automatically selected when the user did not blink their eyes within 3 s after turning on the system. The SSVEP method was selected if the user started to execute the eyeblink switch again within 3 s after turning on the system. The Eye Writing method was selected if the user executed the eyeblink switch twice. Fig. 2 illustrates the flowchart of this process.

(iii) *Device selection methods.* The methods employed to select the target device to control are as follows:

(a) *Image Recognition method.* Maintaining a gaze at an image card attached to each device for 2 s allowed the participants to select the device. The image recognition on Hololens was realized with a toolbox called Vuforia in Unity 3D (Unity Technologies ApS, San Francisco, CA, USA), with the image received through a built-in camera of Hololens. Fig. 3(a) illustrates the image cards attached to each device. In our experiment, a total of five home appliances (TV, air purifier, humidifier, heater, and audio) were prepared.

(b) *SSVEP method*. The user could select the device to control by staring at one of the five visual stimuli flickering at different frequencies, each having an icon representing the device to be controlled, as depicted in Fig. 3(b). Accordingly, the device could be selected based on the SSVEP detection algorithm (EMSI) as described previously. Based on the optimal window size determined in the offline experiment, the duration of stimulus presentation was set to 3 s.

(c) *Eye Writing method*. The user could select the device by writing a pattern of a number designated for each device, using their ocular movement. Consequently, the eye-writing patterns could be identified based on the EOG-based eye-tracking introduced in [22], which provides a detailed description on the method. Accordingly, five number patterns were employed in the present experiment. Moreover, the user could also write an eye-writing pattern corresponding to '0' to show a 'help' window which will remind all the number patterns (see Fig. 3(c)). The 'help' display was visualized for 5 s before it disappeared. During the eye-writing recognition session, nine guide dots were visualized on the AR display lasting for 5 s (see Fig. 3(d)). The movement of the eyes was reconstructed from the horizontal and vertical EOG components and the pattern that best matches the predefined symbolic patterns was selected [22].

(iv) *Command selection.* Once the user selected a device to control using one of the three device selection methods, the user could then execute the control commands of the device by staring at the visual stimuli, as described in the '(iii) Device selection methods – (b) SSVEP method' section. In total, five visual stimuli were presented, which comprised four control commands and one 'back' command to directly return to the device selection stage (see Fig. 4), except for the TV control. However, the 'back' command was not provided with in the command selection stage in TV control which required five control commands; the user needed to turn off and turn on the system by serially executing the eyeblink switch to select other devices during TV control. In each trial, the visual stimuli were presented for 3 s with an ISI of 7 s. The command selection trials were repeated until the user turned off the system by executing the eyeblink switch, thereby allowing the user to control the selected device as intended. Once the command selection session was completed, the participants could turn off the entire system by executing the eyeblink switch and returning to the idle state. Fig. 2 presents the overall structure of the system operation. In our experiments, the control commands were transmitted to

TABLE I
PRESENTED COMMANDS OF EACH HOME APPLIANCE IN 'COMMAND SELECTION' STAGE

| Home Appliance | Commands | | | | |
|---|---|---|---|---|---|
| TV | On/Off (Toggle*) | Volume Up | Volume Down | Channel Up | Channel Down |
| Air Purifier | On/Off (Toggle*) | Wind-auto Mode | Wind-turbo Mode | Sleep Mode | Back |
| Humidifier | On/Off (Toggle*) | Wind-auto Mode | Wind-turbo Mode | Sleep Mode | Back |
| Audio | On/Off (Toggle*) | Play/Pause | Volume Up | Volume Down | Back |
| Heater | On/Off (Toggle*) | Temperature Up | Temperature Down | Wind Mode Change | Back |

* The on/off command functioned as a toggle switch, according to the device status.

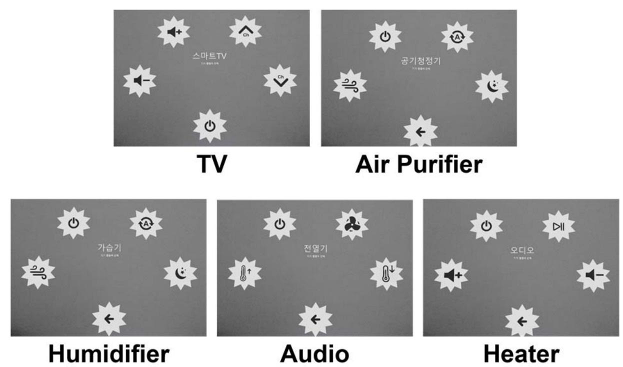


Fig. 4. The visual stimuli presented in the command selection stage. The visual stimuli corresponding to the selected device was presented in the AR display. Each stimulus was represented by intuitive icons representing different control commands.

the devices using one of the following two methods: i) Internet of things (IoT) and ii) Infrared (IR) remote controller. Because the humidifier and air purifier were devices embedded with IoT function, they were controlled wirelessly via a custom software developed using Samsung IoT device control application programming interface (API) (Samsung Electronics, Co. Ltd., Seoul, South Korea). Devices that were incompatible with IoT were controlled using an IR transmitter embedded in an Arduino microcontroller. The control commands for each device control are presented in Table I.

*4) Online Experimental Paradigm:* The online experiment comprised three sessions, each with two blocks. For each session, the participants were instructed to use one of the three device selection methods to select the device to control, and to select and control a device for each block. Consequently, each participant used all three device selection methods throughout the experiment and controlled all five devices by performing total six blocks. In each block, participants were instructed to

i) switch on the HA system, ii) select the given device selection method, iii) select the designated device to control, iv) execute control commands according to the pre-instructed order, and v) turn off the system. If the device exhibited malfunctions due to an unintended command mistakenly selected by a participant or a mis-classification of SSVEP responses, then the participant had to correct the false operation and complete the remaining tasks. For example, assume that the given task was to select heater and execute “temperature up” command. If the heater was turned off by participant mistakenly or due to a misclassification, then the participant had to turn the heater back on by staring at the stimulus with “on/off” icon and then stare at the “temperature up” stimulus again to complete the task. In another example, if the given task was to select the air purifier but TV was selected, then the participant could go back to the previous stage (device selection stage) by staring at the stimulus with “back” icon and select the air purifier again. Alternatively, the participant could simply turn off the system and turn it on again using eyeblink switch, and then select the air purifier in the device selection stage. The participants managed to tackle the problematic situation according to their own preferences. The minimal number of trials required to complete each block in the command selection stage was six for TV, and five for the other four devices. Each participant was given approximately 10 min to familiarize themselves with the device determination methods and the proposed HA system before the experiment, and then instructed on the designated device selection method, device, and commands prior to each session.

After finishing each session, the participants watched a YouTube video for approximately 4 min to investigate the time needed to operate the eyeblink switch and the possible false positive rate (FPR) of the eyeblink switch. To measure the time needed to operate the eyeblink switch, the participants were asked to operate the switch whenever the video paused by the experimenter at three random time points. Once four eyeblinks were successfully detected for switch operation, the experimenter played the video again. The operation of the switch while watching the video was counted as a false operation of the switch.

Once the entire experiment concluded, the participants were asked to fill a questionnaire called system usability scale (SUS) to evaluate usability of the proposed system. In the experiment, the Korean version of the questionnaire [23] were provided, since all participants were native Koreans. A demonstration video clip of the proposed HA system can be found in the following link: https://youtu.be/qJkPxU-0m38.

## III. Results

### A. Experiment I–Offline Experiment to Determine Optimal Duration of Visual Stimulation and Individualized Electrode Configuration

To determine the optimal duration of visual stimulation, the classification accuracy and ITR were evaluated using different window sizes with the universal and individually selected electrodes (see Fig. 5). First, we tested the statistical significance of the performance difference between the universal and individualized electrode configurations, using a Bonferroni-corrected Wilcoxon signed rank test. The individually selected electrodes showed significantly improved performance compared to the universal electrodes set for many window sizes, in terms of both the classification accuracy and ITR. The list of the individually selected electrodes sets for each participant and the grand averaged SSVEP response are presented in the Table V and Fig. 8 of Appendix section, respectively.

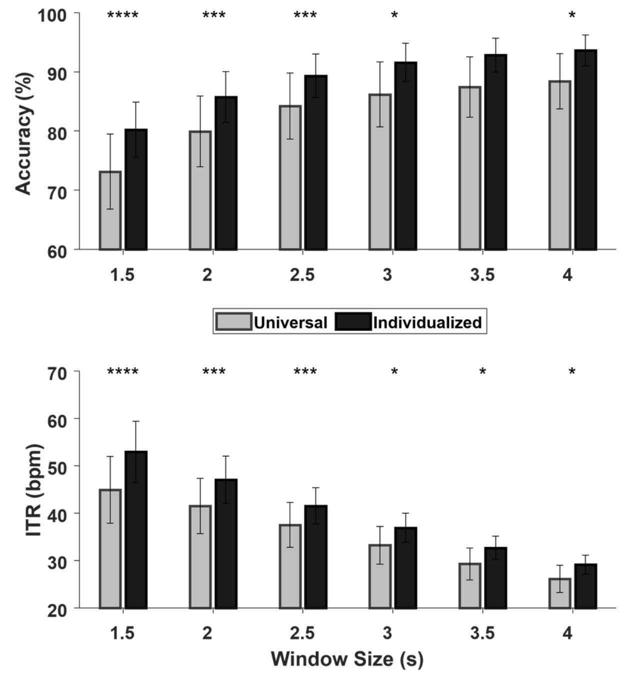


Fig. 5. Comparison of the mean classification accuracy and ITR calculated with universal and individualized electrode configurations, with respect to different window sizes. (*$p < 0.05$, ***$p < 0.005$, ****$p < 0.001$, Bonferroni-corrected Wilcoxon signed rank test).

In this study, we selected 3 s as the optimal duration of stimulus presentation, which was primarily based on the following two observations. First, a higher ITR can be achieved with a shorter window size since ITR is in inverse proportion to window size. Second, although the ITR was higher with a shorter window size, the classification accuracy with the shortest window size, i.e., 1.5 s, was only 80.2%. In contrast, the classification accuracy for a window size of 3 s was 91.6%, which was considered to be sufficiently high with a classification accuracy comparable to that with the window size of 4 s (93.6%). It should be noted that the classification accuracy was almost saturated for window sizes larger than 3 s.

### B. Experiment II– Online Home Appliance Control

The classification accuracy and ITR achieved in the online home appliance control experiments are listed in Table II. All participants successfully completed the experiment. In the table, the parameter ‘Total Trials’ represents the number of trials each participant performed to complete the experiment. Meanwhile, ‘Correct Trials’ represents the number of the trials in which the pre-instructed devices or commands were selected correctly by the participant, while ‘Incorrect Trials’

TABLE II
SSVEP CLASSIFICATION PERFORMANCE IN EXPERIMENT II

| Subject | Total Trials | Correct Trials | Incorrect Trials | Accuracy (%) | ITR (bits/min) |
|---|---|---|---|---|---|
| P1 | 60 | 42 | 18 | 70.0 | 16.8 |
| P2 | 55 | 39 | 16 | 70.9 | 17.4 |
| P3 | 38 | 36 | 2 | 94.7 | 38.4 |
| P4 | 36 | 35 | 1 | 97.2 | 41.7 |
| P5 | 34 | 34 | 0 | 100 | 46.4 |
| P6 | 34 | 34 | 0 | 100 | 46.4 |
| P7 | 50 | 38 | 12 | 76.0 | 20.9 |
| P8 | 34 | 34 | 0 | 100 | 46.4 |
| P9 | 43 | 37 | 6 | 86.0 | 29.2 |
| P10 | 34 | 34 | 0 | 100 | 46.4 |
| P11 | 45 | 34 | 11 | 75.6 | 20.6 |
| P12 | 40 | 36 | 4 | 90.0 | 33.1 |
| P13 | 36 | 34 | 2 | 94.4 | 38.0 |
| **Mean** | | | | **88.8±3.3** | **34.0±3.3** |

TABLE III
PERFORMANCE OF EYEBLINK-BASED SWITCH IN EXPERIMENT II

| Subject | Time elapsed to switch on/off (s) | FPR (times/min) | FPR (times/hour) |
|---|---|---|---|
| P1 | 2.3 | 0.19 | 11.50 |
| P2 | 3.9 | 0 | 0 |
| P3 | 8.7 | 0.14 | 8.65 |
| P4 | 6.5 | 0.28 | 16.76 |
| P5 | 4.3 | 0.08 | 4.78 |
| P6 | 5.6 | 0 | 0 |
| P7 | 5.5 | 0.03 | 2.07 |
| P8 | 2.4 | 0 | 0 |
| P9 | 2.5 | 0.11 | 6.71 |
| P10 | 4.3 | 0.04 | 2.40 |
| P11 | 2.4 | 0.11 | 6.86 |
| P12 | 2.2 | 0 | 0 |
| P13 | 2.3 | 0.08 | 5.05 |
| **Mean** | **4.1±1.0** | **0.08±0.02** | **4.98±1.42** |

corresponds to the number of misclassified trials. The number of trials differed across participants because each participant had different numbers of errors and adopted their own strategy to correct the wrong operation. The classification accuracy was evaluated by dividing the number of correct trials by the number of total trials (correct trials) / (total trials). The classification accuracy and ITR were 88.8% and 34.0 bits/min on average, respectively.

Table III lists the overall performance of the eyeblink switch. Evidently, the time of 4.1 s was required to operate the eyeblink switch on average, although the switch was designed to operate by the detection of four eyeblinks within 3 s. It should be noted that this result does not imply that the participants failed to operate the switch, instead, it infers that the participants occasionally had difficulty blinking rapidly for the first 3 s, and thus they had to keep blinking a few more times. Consequently, the first time point where the four eyeblinks were detected within recent 3 s was 4.1 s on average. The FPR of the eyeblink switch was 0.08 times per minute, or 4.98 times per hour on average. During the online experiment, if the status of the system was changed by a false operation of the eyeblink switch, the participants had to return to the designated stage by executing the eyeblink switch again by repeatedly blinking their eyes.

Figure 6 illustrates the accuracy of device selection through the EOG-based eye writing recognition for each participant.

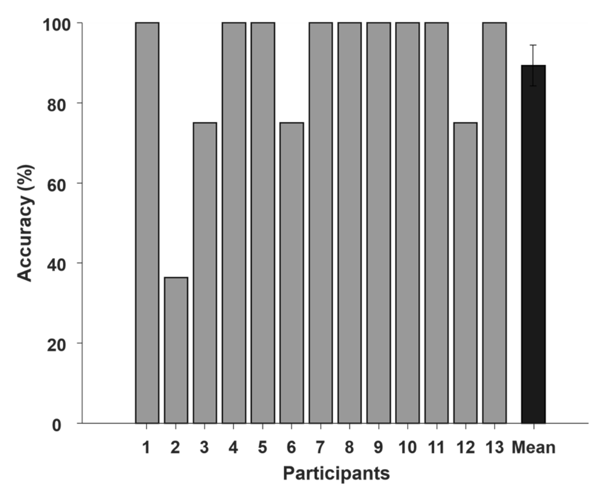


Fig. 6. Classification accuracy of device selection using the eye writing.

Reportedly, the classification accuracy was 89.3% on average, with most participants managing to select a device with 100% accuracy, three participants exhibited 75% accuracy and only one participant exhibited 36.4% accuracy. Importantly, the accuracy of device selection through image recognition was 100% for all participants.

The usability of the proposed system investigated using SUS is presented in Table IV. The SUS score ranges between

TABLE IV
COMPARISON OF PERFORMANCE WITH PREVIOUSLY REPORTED BCIS TO CONTROL EXTERNAL DEVICE FOR THE ELDERLY

| Study | BCI paradigm | Age of participants | SUS score | Accuracy (%) | ITR (bits/min) | Necessity of calibration |
|---|---|---|---|---|---|---|
| Simon *et al.* [40] | Auditory P300 | 66 | 82.5 | 47 | 6.1 | Y |
| Schettini *et al.* [38] | Visual P300 | 60 | 80.3 | 91 | <10 | Y |
| Pasqualotto *et al.* [39] | Visual P300 | 56.5 | 71.2 | N/A | 8.7 | Y |
| Proposed system | SSVEP | 67.5 | 71.2 | 88.8 | 34.0 | N |

0 and 100, with 0 representing the poorest usability and 100 reflecting the best usability. The investigated SUS score for the proposed HA system was 71.2, ranging between 45 and 92.5. Even though an absolute criterion does not exist for evaluating the SUS scores, the SUS score of 70 on average was proposed as an acceptable minimum according to the original literature related to SUS [24].

## IV. DISCUSSION

With the recent advances in medicine, healthcare, and therapeutics, the general life expectancy of the population is gradually increasing. Consequently, the social burden of caring for the elderly is becoming a serious problem [25]. Admittedly, various assistive technologies have been proposed to aid the elderly accomplish their daily life activities, e.g., an exercise monitoring system using user's physiological signals [26]. However, there has been no such system to control home appliances in a hands-free manner with reliable performance, which can assist the elderly to live without a caregiver at home. Moreover, it has been also reported that using such smart home systems for the elderly can improve their health conditions and their independence [27]. However, despite recent advances in neural engineering and signal processing fields, no BCI study controlling external devices has demonstrated a practical performance level and usability with the elderly. In the present study, the authors strived to overcome the shortcomings of the previous BCIs by combining AR-HMD with SSVEP-based BCI and EOG-based eye-tracking and by designing a system architecture that allows these end users to select devices with a preferred method. Furthermore, the employment of AR-HMD has given mobility and flexibility to the proposed HA system by ensuring that the users no longer have to stay in front of the screen to present visual stimulus in conventional BCI systems.

In the present study, AR, BCI, and IoT technologies were combined to develop a real-time home appliance control system for the elderly. Subsequently, we evaluated the performance and usability of the proposed system involving people aged over 65 years. In the offline experiment, the optimal duration of visual stimulation and individualized electrode configurations were determined. Subsequently, we developed an online SSVEP-based BCI system using the experimental conditions determined in the offline experiment. The implemented online home appliance control system provided users with various interfacing options by combining image recognition, EOG-based eye writing, and the eyeblink-based switch with the conventional SSVEP-BCI system. The experimental results revealed that all elderly participants successfully controlled five home appliances with the proposed HA system, suggesting that the proposed system has potential to be utilized in practical scenarios.

The performance of the proposed HA system was compared with those of previous BCI-based external environment control systems targeted to the older adults, as presented in Table IV. To the best of our knowledge, the performance of the device control system in this study surpassed the best results reported in the literature on BCIs for external device control for the elderly, in terms of both accuracy and ITR. Although the system proposed by Schettini et al. showed higher accuracy than the proposed HA system, the ITR of their system was significantly lower than that of our system. Most importantly, the proposed system does not require any calibration session, whereas most of the BCIs reported in previous literature required a calibration session to train a classifier. Although the authors used individualized electrode configurations to enhance the overall performance of the system, the performance with the universal electrode configuration (O1, Oz, and O2) was also sufficiently high to be employed in practical home appliance control applications (Fig. 5). Although some previous studies reported higher SUS than ours, it is expected that the usability of the proposed system may be further enhanced by employing control functions based on the pre-experimental survey with the participants or by incorporating additional functions into the HA system such as communication and PC applications [38].

Although the average SSVEP classification accuracy was higher than 90% for a 3 s window size in the offline experiment, the average accuracy was only 88.8% in the online experiment even when the same window size was used. It has been frequently reported that the BCI performance in online sessions was higher than that in offline or calibration sessions for various reasons, including the training effect [28], [29], [30]. However, unlike previous literature that compared the performances in offline and online BCI experiments, the experimental paradigm employed in the online experiments in this study was even more complex than that for the offline experiment. Indeed, many additive functions including image recognition, eye writing, and eyeblink switch were employed during online experiments, all of which the participants had not experienced in the previous offline experiment. Moreover, the BCI performance might be affected by the circumstance of the online experiment because the participants had to complete the pre-instructed task based on their own decision when a false operation occurred. Indeed, the degradation of BCI performance due to an increased cognitive workload has been frequently reported [31].

In the online experiment, on average, the eyeblink switch required 4.1 s to operate the switch, and the averaged FPR of the switch was 4.98 times per hour. Compared to our previous study [7], in which younger people participated and an average FPR of 0.89 times/h was achieved with the same eyeblink switch, this result revealed considerably degraded performance. Indeed, the participants in this study occasionally struggled to repeatedly blink their eyes within such a short period, although they had no problem in their ordinary blink. This phenomenon is presumably attributed to the age, which is primarily based on the reports that the functionality of eyelids of older population is reduced compared to younger population [32], [33]. Moreover, it has been reported that older population takes longer in spontaneous eye blinking as well as in intentional eyeblinks [32], [33], [34]. Nevertheless, in the online experiment of this study, all the participants successfully determined the device selection method using the eyeblink switch, and could complete the designated task by switching on and off the HA system using the eyeblink switch even when unexpected false operations occurred. In this study, the main target subjects were the elderly, not the patients with locked-in syndrome, but it is expected that our hybrid EEG and EOG system can also be applied to some patients with amyotrophic lateral sclerosis (ALS) because the oculomotor function is generally the last motor-related function remaining in those with severe ALS.

The individually selected electrode sets for each participant and the topographical distribution for the number of selections of each electrode are presented in Table V and Fig. 7 in the Appendix section, respectively. Although O1, Oz, and O2, the traditional electrode set widely employed for SSVEP-based BCIs were most frequently selected, it is noteworthy that P7 showed remarkable number of selections while P8 was rarely selected. This result might be in line with a previous report that showed motion-evoked P300 amplitude was significantly larger in the left hemisphere than in the right hemisphere [35], although further investigations are still needed.

The average SUS score for the proposed HA system was shown to be approximately 71. It is a score that satisfies the minimum acceptance level suggested by the original literature proposing SUS [24]. Based on the studies by Kortum et al. [36], [37], in which the usability of various daily products and mobile applications were investigated using SUS, the score of the proposed HA system is higher than Excel (SUS score: 56.5; Microsoft, Corp., Redmond, WA, USA), lower than Microwaves (SUS score: 86.9), and similar to Skype (SUS score: 71; Microsoft Corp., Redmond, WA, USA). In addition, a study reported that the conventional control interfaces such as mouse and buttons scored SUS of 84 on average with

TABLE V
INDIVIDUALLY SELECTED ELECTRODE SETS FOR EACH PARTICIPANT

| Subject | Channels | Participated Experiments |
|---|---|---|
| P1 | Pz, O1, Oz | I, II |
| P2 | P7, Oz, O2 | I, II |
| P3 | P7, P3, Oz | I, II |
| P4 | P7, P8, Oz | I |
| P5 | P7, O1, Oz | I, II |
| P6 | O1, Oz, O2 | I, II |
| P7 | O1, Oz, O2 | I |
| P8 | Pz, P8, Oz | I |
| P9 | P3, Oz, O2 | I, II |
| P10 | P7, P3, PO4 | I, II |
| P11 | P7, POz, O1 | I |
| P12 | P7, Pz, Oz | I, II |
| P13 | O1, Oz, O2 | I, II |
| P14 | P7, P4, O1 | I, II |
| P15 | Pz, Oz, O2 | I |
| P16 | P7, P4, O1 | I, II |
| P17 | P8, O1, Oz | I, II |
| P18 | O1, Oz, O2 | I, II |
| P19 | P3, P8, POz | I |

elderly participants [38]. Given that most of the BCI studies focus on methodological aspects while neglecting usability aspects [39], enhancing the usability of the proposed HA system could be an interesting research topic that has to be pursued in the future study. The usability of the proposed system may be enhanced by i) employing control functions preferred by participants via a pre-experimental survey, or ii) adding functions such as communication as in [38].

Although presentation of visual stimulus is inevitable in SSVEP-based BCI systems, the usability of the visual stimulation method in the proposed system was not evaluated, which includes fatigue caused by visual stimulation. Reportedly, a motion-reversal stimulus caused less fatigue and mental workload compared to a flickering stimulus in a previous study [41]. The comfortability of the visual stimulus adopted in the present study and GSS that changes its size and luminance concurrently has not yet been investigated, the usability of this relatively new type of stimulus should be evaluated in

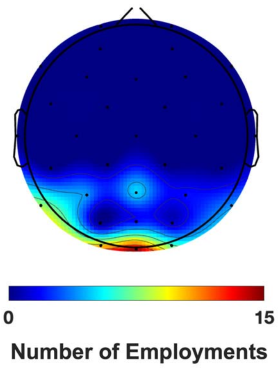


Fig. 7. Topographical distribution of the number of employments for individually selected electrode set in Experiment I.

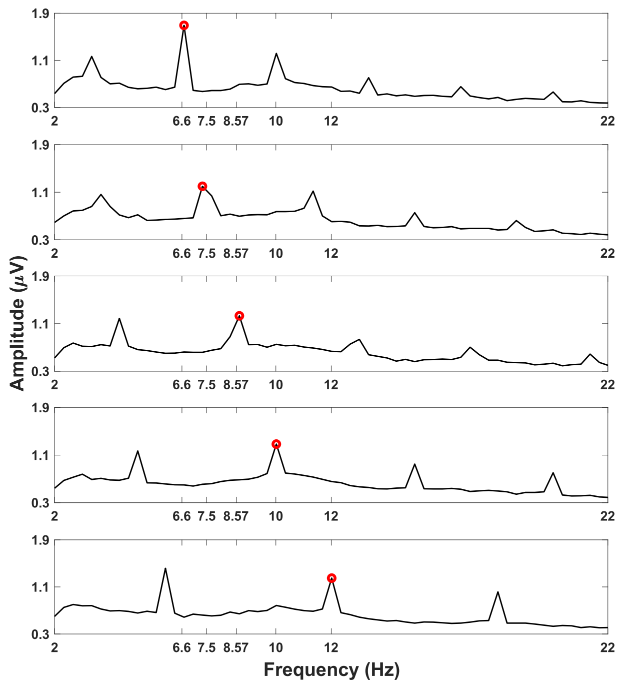


Fig. 8. The grand-averaged spectral amplitude of the data recorded in Experiment I. Each row shows the data with stimulation frequencies of 6.6, 7.5, 8.57, 10, and 12 Hz. Please note that not only the SSVEP response at the fundamental frequency but also the SSVEP responses at the subharmonic and the harmonic frequencies were clearly elicited.

a future study. Furthermore, as AR and IoT are cutting-edge technologies, their usability and user acceptance are also crucial aspects. Indeed, various applications for the elderly using AR and IoT have been recently developed and the usability of the applications, such as friendliness and comfort, has also been investigated and has received positive responses [42], [43], [44], [45]. For example, Aruanno et al. developed a cognitive training program in AR environment using Hololens before evaluating its usability for people with 64–67 years old, reporting that the task achievement was independent of their familiarity to the technology or technological knowledge. Relatively, even people who never used a computer could correctly accomplish all the given tasks, owing to the intuitive interaction methods provided by Hololens [44]. As an another example, Lera et al. [42] developed a software to instruct drug dose in AR environment and evaluated its usability with people aged 59–90, and the averaged 'AR usefulness' and 'AR friendliness' scores were 4.4 and 3.8 out of 5, respectively. Reportedly, the elderly accommodated the necessity of IoT technology and presented a high level of willingness, after acquiring sufficient awareness about the benefits of IoT [45]. Moreover, as the technologies are still in early stages of development, the usability is expected to be further enhanced in the future.

## Appendix

Table V and Figs. 7 and 8 are included in this Appendix section.

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