

# Brainy Home: A Virtual Smart Home and Wheelchair Control Application Powered by Brain Computer Interface

Cihan Uyanik<sup>1</sup><sup>a</sup>, Muhammad Ahmed Khan<sup>1</sup><sup>b</sup>, Rig Das<sup>1</sup><sup>c</sup>, John Paulin Hansen<sup>2</sup><sup>d</sup>  
and Sadasivan Puthusserypady<sup>1</sup><sup>e</sup>

<sup>1</sup>Department of Health Technology, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark

<sup>2</sup>Department of Technology, Management and Economics, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark

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**Abstract:** In recent years, smart home applications have become imperative to improve the life quality of people, especially for those with motor disabilities. While the smart home applications are controlled with interaction tools such as mobile phones, voice commands, and hand gestures, these may not be appropriate for people with severe disabilities that impacts their motor functions, for instance locked-in-syndrome (LIS), amyotrophic lateral sclerosis (ALS), cerebral palsy, stroke, etc. In this research, we have developed a smart home and wheelchair control application in a virtual environment, which is controlled solely by the steady-state visual evoked potential (SSVEP) based brain computer interface (BCI) system. It is a relatively low cost, easy to setup wireless communication protocol, which offers high accuracy. The system has been tested on 15 healthy subjects and the preliminary results comprehensively show that all the subjects completed the device interaction tasks with approximately 100% accuracy, and wheelchair navigation tasks with over 90% accuracy. These results clearly indicate that in future, the developed system could be used for real-time interfacing with assistive devices and smart home appliances. The proposed system, thus may play a vital role in empowering the disabled people to perform daily-life activities independently.

## 1 INTRODUCTION

Neural disorders, such as stroke, can cause long-term or even permanent disability, resulting in detrimental social and economic effects. Approximately 25.7 million stroke survivors in the World (Johnson et al., 2019) demand assistance as they suffer from lack of interaction ability due to their physical limitations. This makes them highly dependent on caregivers, even with their daily activities on a regular day. Thus, the development of portable and easy-to-use assistive systems is crucial as well as important. Such systems obviously may empower the disabled to live independently.

Advancements in internet enabled devices (IoT) have facilitated smart home systems (Del Rio et al., 2020). Although there are numerous applications

within this field, almost all of them are highly dependent on mobile phones or other type of interaction systems such as voice commands, hand gestures, etc. However, people who have serious motor control challenges (in consequence of, for example, locked-in-syndrome (LIS), amyotrophic lateral sclerosis (ALS), cerebral palsy, stroke, and spinal-cord injuries) are restricted from taking full advantage of the available home automation technologies.

Brain computer interface (BCI) based control methodologies, by exploiting the subjects' electroencephalogram (EEG) signals to control external devices, have had significant progress in recent years. In such systems, the target brain responses/activities is measured and a decision-making system is implemented to interact with the external devices (Mistry et al., 2018). This allows support to people who have difficulties to complete the tasks physically (Zhuang et al., 2020). Development of BCI assisted devices have greatly attracted the scientific community with a motivation to help people who especially demands assistance in daily tasks because of their health limitations (Belkacem et al., 2020).

EEG-BCI systems are based mainly on three paradigms: P300, motor imagery (MI), and steady-state visual evoked potential (SSVEP). Out of these three types, the SSVEP based systems tend to become dominant in real world applications due to their high bandwidth, minimal training time, and faster calibration (Faller et al., 2017). Additionally, the use of external stimulus source allows to integrate multiple techniques such as augmented reality (AR), eye tracking, etc. (Putze et al., 2019). In (Saboor et al., 2017), the authors have developed a SSVEP-BCI system, which was stimulated by AR glasses, and successfully achieved over 85% accuracy on the designed control tasks, including elevator, coffee machine and light switches. Similarly, Park et al. (Park et al., 2020) focused on developing a SSVEP-BCI system with an AR head set. They reported high information transfer rate (ITR) (37.4 bits/min), and high response rate of activation (2.6 seconds) to turn on/off of devices. In another study, Lin and Hsieh (Lin and Hsieh, 2014) developed a television control system and attained almost 99% accuracy with 4.8 seconds command activation time. Adams et al. managed to create a smart home application by SSVEP-BCI system to control six devices with multiple screens placed at different locations inside the environment, and they achieved an average accuracy of 81% (Adams et al., 2019).

Although the aforementioned systems have accomplished and produced significant results, mobility is still a vital concern due to wired, bulky, effort-demanding, and expensive setups, especially in terms of signal acquisition tools. In this paper, we demonstrate a novel, cost-effective, user friendly, and easy to setup wireless SSVEP-BCI control of smart home and wheelchair application through a virtual environment.

## 2 MATERIALS AND METHODS

### 2.1 SSVEP-BCI and Data Acquisition Setup

In SSVEP-BCI systems, a visual stimuli is responsible to present visual triggers, and each of them has unique frequencies. When a user concentrate on one of these visual triggers (named as *flickering patterns*), a neural activation uniquely matching the focused pattern occurs in the visual cortex of the user. These neural activation is measurable via EEG acquisition device, and the acquired signal could be processed to decode the generated unique signature. If any visual pattern is dedicated to perform an action based on the

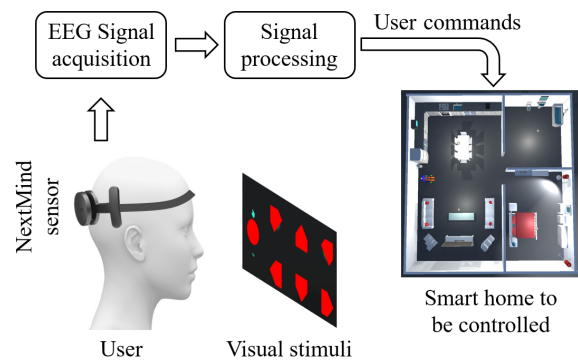


Figure 1: Schematic of SSVEP-BCI system.

current state of the controlled system/environment, an accurate signal analysis scheme produces the correct user commands. The described procedure is depicted in Figure 1.

For the development of a user-friendly and portable BCI system for smart home and wheelchair control application, the selection of a simple and robust EEG acquisition system is of utmost importance. For this, we used the NextMind SSVEP-BCI device, which is non-invasive, compact and has nine high quality dry electrodes covering the visual cortex area of the brain. It contains Bluetooth communication module that wirelessly transmits the acquired EEG signals to the computing unit. The computer acts as a main processing unit that is responsible to run a 3D simulation environment, receive and analyze EEG signals, determine focused control pattern, and record experimental data.

### 2.2 3D Environment for Control Application

Smart home and wheelchair control environment are developed (Figure 2a) in Unity 3D Game Engine<sup>1</sup>. The environment contains a wheelchair and various types of daily life home appliances which are controlled by the user with the BCI setup. This BCI setup contains the NextMind device and SSVEP based input screen installed on the wheelchair (Figure 2b). More details on the developed smart home environment and wheelchair can be found at the provided video link<sup>2</sup>.

Implementation of system software for wheelchair and smart home appliances are completed in C# programming language, which is one of the officially supported development languages of Unity Engine. System software architecture is depicted in Figure 3.

<sup>1</sup><https://unity.com/>

<sup>2</sup><https://youtu.be/PqelTCLJ77U>

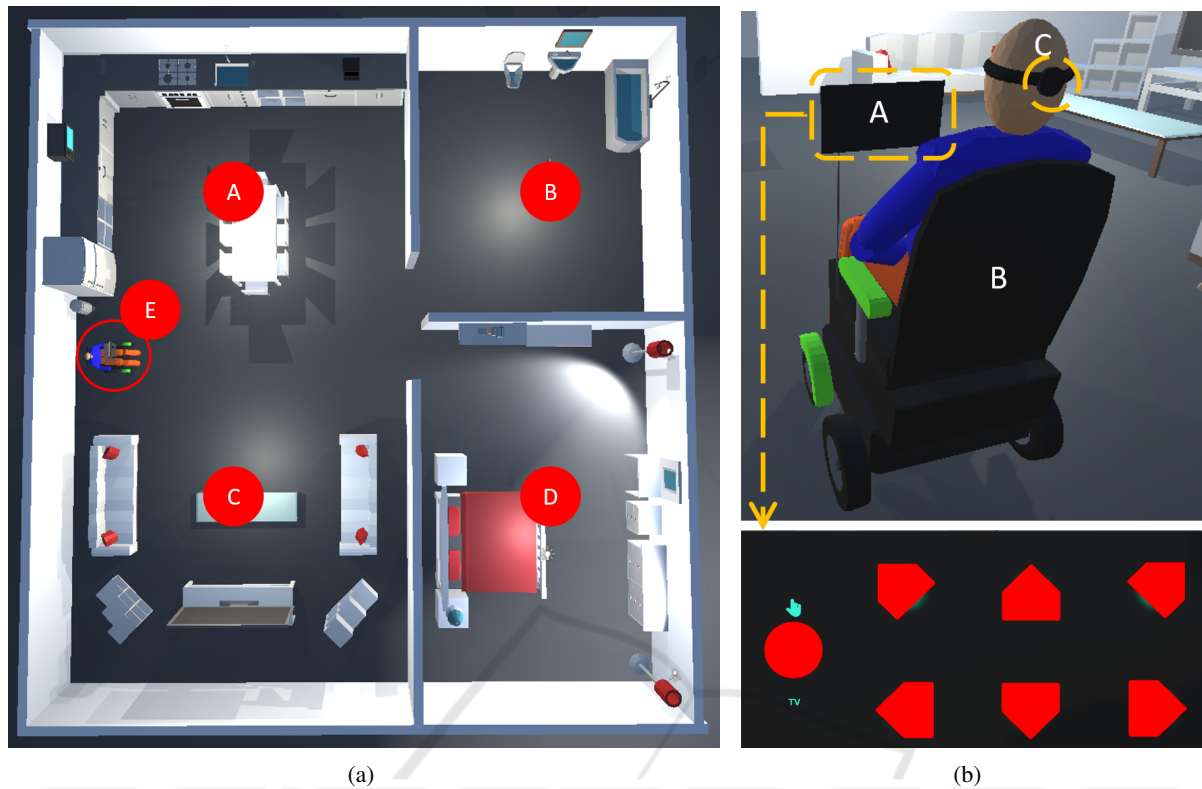


Figure 2: (a): Smart home environment (A: Kitchen, B: Bathroom, C: Living room, D: Bedroom, E: Subject on the wheelchair with NextMind device), (b): Wheelchair and subject (A: Control display, B: Wheelchair, C: NextMind device).

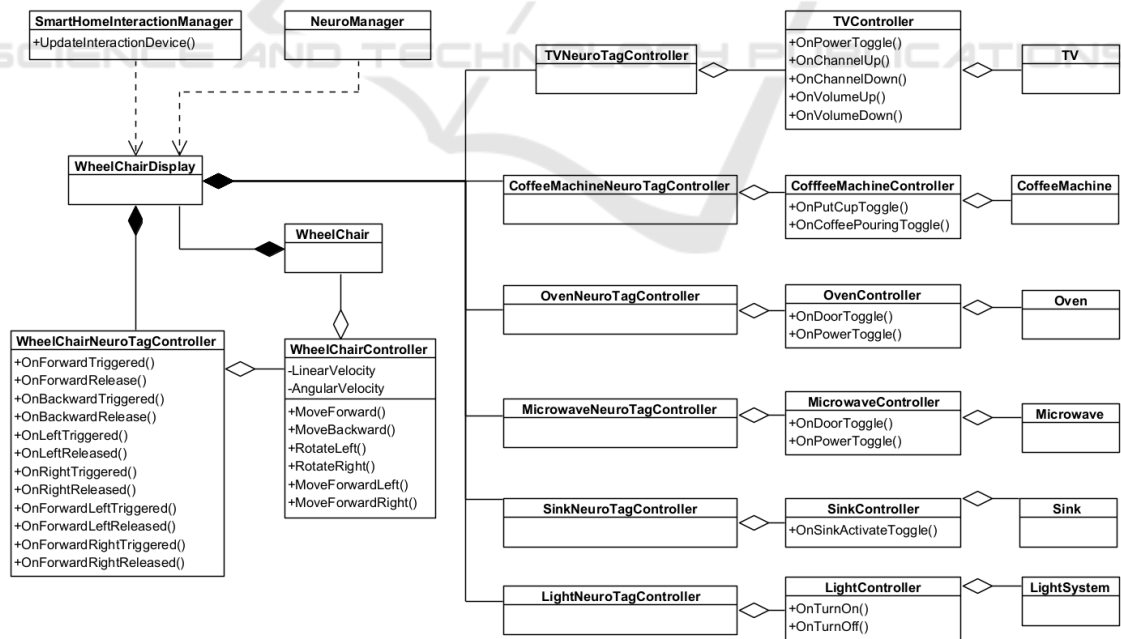


Figure 3: Software architecture of the smart home and wheelchair control system.

In order to preserve simplicity of the diagram, only the most important classes and their crucial functionalities are demonstrated in the class blocks.

As seen from the class diagram, all smart home environment appliances and wheelchair are controlled by *WheelChairDisplay*, which is the primary interaction device of the user, who wears the NextMind SSVEP-BCI acquisition device. *SmartHomeInteractionManager* is responsible to keep the control display valid in terms of available interaction patterns. When the wheelchair is close to a BCI controllable appliance (television, coffee machine etc.), it forces the display to show a sub-control menu selection pattern as shown in Figure 2b.

When the subject focuses on a control pattern (red patterns on display) to start an action, *NeuroManager* triggers the corresponding *NeuroTagController* such as the *WheelChairNeuroTagController*, and the *TVNeuroTagController*. Finally, the input signal for relevant device controller (*WheelChairCintroller*, *TV-Controller*) are delivered, and the demanded action by the user (via brain signals) is performed by the device.

## 2.3 Participants

Fifteen healthy control subjects (three females and twelve males with a mean age of  $30 \pm 8$ ) voluntarily participated in the experiments. Two of them have prior experience with the BCI systems, and the rest of them are naïve.

## 2.4 Experimental Design and Procedures

Three sets of experiments are designed to test the subjects' performance for controlling smart home appliances and wheelchair navigation in the virtual environment via the BCI system. In each trial of an experiment, the ultimate expectation from a participant is to complete the active trial as fast as possible. All experiments consist of *wheelchair navigation task* combined with a *device control task*. While subjects are conducting experiments, their focus states on navigation patterns, corresponding wheelchair motions, external device control focus commands and relevant timing information are recorded for further analysis.

### 2.4.1 Experiment 1

This is the simplest of all 3 experiments. The objective is to move the wheelchair into the bedroom by focusing navigation control patterns located on the display (see Figure 2b). Figure 4 shows a completed trial and wheelchair's path. Transparent spheres shown in

the figure indicate subsection waypoints of the trial. In addition to the navigation task, the subject must turn on bedroom light when the related control pattern appears on the control display. In a real-life smart home, this would be implemented by position-based proximity interaction (Ballendat et al., 2010). This extra interaction task is considered as an added distraction and increases the complexity of the overall trial. Video demonstration of this experiment is provided in<sup>3</sup>.

### 2.4.2 Experiment 2

In experiment 2, the user has to complete a relatively complex navigation task, which has three waypoints as shown in Figure 5a. At the end of the navigation task, subject must do a coffee machine interaction task as shown in Figure 6a. In order to complete this task, the subject must focus on the patterns in the order of B-C-C-B-A. This experiment is demonstrated in<sup>4</sup>.

### 2.4.3 Experiment 3

It is the most complicated one, having series of navigation control actions. The tracking path starts from the same location as in the first and second experiments, and ends in front of the television. In this task (Figure 5b), the path contains eight waypoints which must be visited. Upon completing the navigation task, a television interaction task (shown in Figure 6b) is presented to the subject. The expected control order must be B-D-F-E-C-B-A. Detailed demonstration of this experiment can be found in<sup>5</sup>.

## 3 RESULTS AND DISCUSSION

The experiments are repeated 3 times for each subject, and the trials are recorded to analyze the overall system performance for each subject. Task completion time (TCT(s)) and task commanding success (TCS(%)) constitute the evaluation basis of the experiments.

### 3.1 Task Completion Time and Closeness

For a subject carrying out one of the experiments, the average of trials' duration is the TCT, which are provided in Tables 1 and 2.

<sup>3</sup><https://youtu.be/C3He41Whems>

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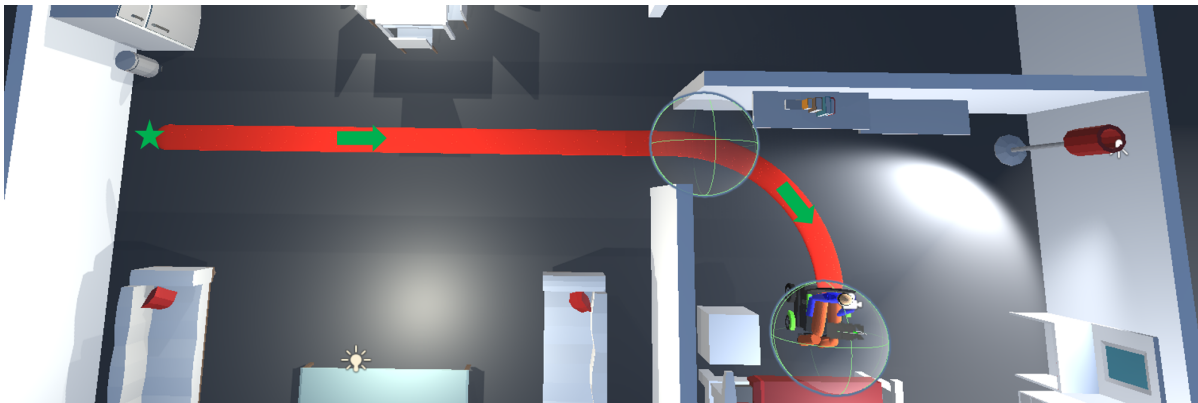
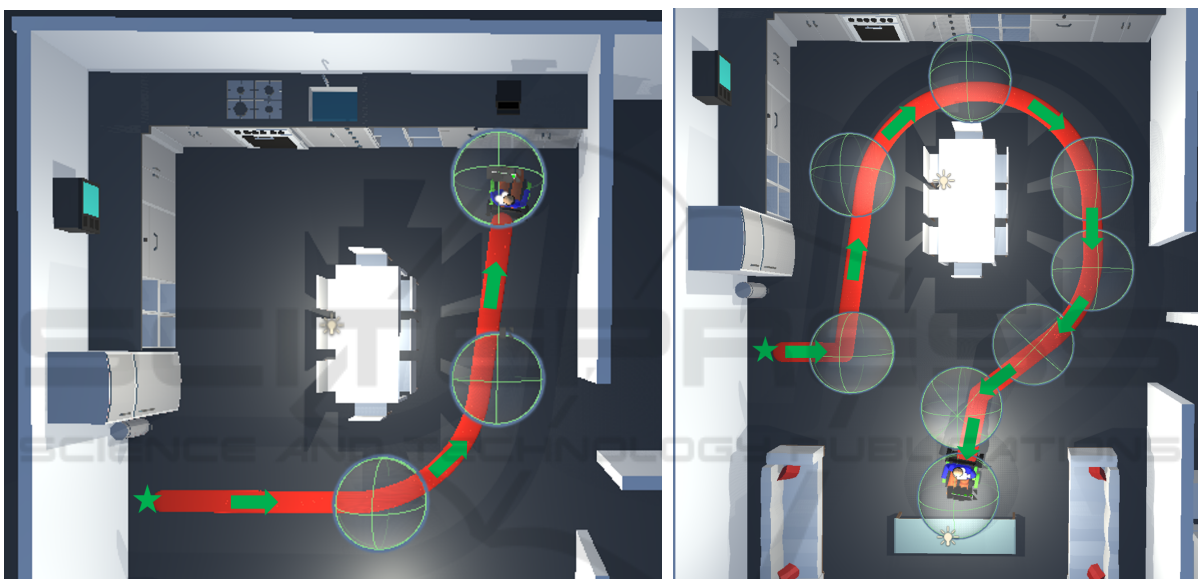


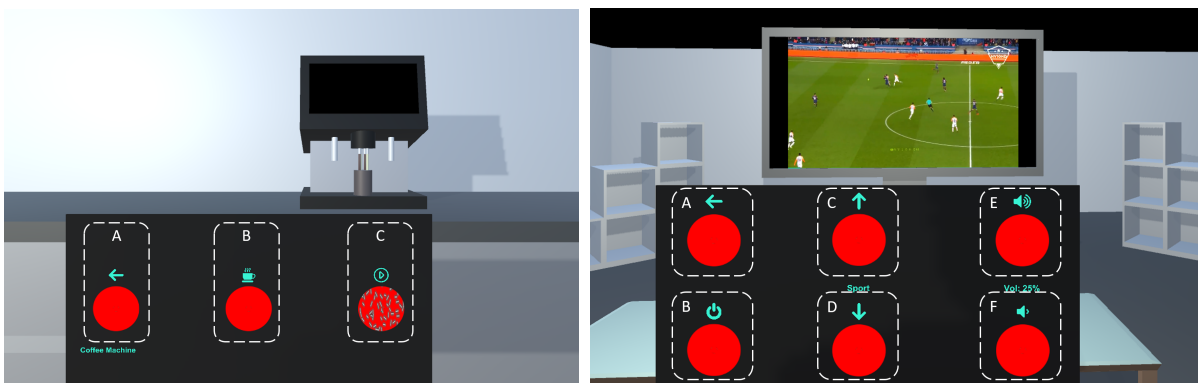
Figure 4: Experiments 1 navigation task (Spheres: Internal waypoints, Red lines: Motion trajectory, Green Arrows: Movement direction).



(a)

(b)

Figure 5: (a) and (b): Experiments 2 and 3 navigation tasks (Spheres: Internal waypoints, Red lines: Motion trajectory, Green Arrows: Movement direction).



(a)

(b)

Figure 6: (a): Experiment 2 Interaction task - Coffee machine (A: Return to wheelchair navigation control, B: Put/Remove coffee mug onto/from the tray, C: Start/Stop filling coffee and milk). (b): Experiment 3 Interaction task - Television (A: Return to wheelchair navigation control, B: Power On/Off Television, C/D: Next/Previous channel, E/F: Volume Up/Down).

Table 1: Results for Experiment 1.

	TCT(s)	CLS(%)	TCS(%)	$E_{traj}(m)$
<b>R</b>	33.4	-	-	-
<b>S<sub>1</sub></b>	34.5	96.6	97.8	0.15
<b>S<sub>2</sub></b>	35.5	93.4	97.9	0.15
<b>S<sub>3</sub></b>	35.8	92.8	98.6	0.19
<b>S<sub>4</sub></b>	36.8	89.7	97.8	0.15
<b>S<sub>5</sub></b>	39.0	83.1	99.7	0.09
<b>S<sub>6</sub></b>	37.7	87.0	97.8	0.15
<b>S<sub>7</sub></b>	35.0	95.0	97.4	0.20
<b>S<sub>8</sub></b>	38.7	83.8	99.3	0.20
<b>S<sub>9</sub></b>	37.0	88.9	97.8	0.16
<b>S<sub>10</sub></b>	36.7	89.8	97.8	0.15
<b>S<sub>11</sub></b>	33.9	98.3	99.3	0.24
<b>S<sub>12</sub></b>	43.9	68.4	97.1	0.29
<b>S<sub>13</sub></b>	33.6	99.2	98.5	0.20
<b>S<sub>14</sub></b>	36.2	91.6	98.8	0.06
<b>S<sub>15</sub></b>	37.9	86.5	99.3	0.19
<b>Avg</b>	36.8	89.6	98.3	0.17

In order to obtain the reference baseline, the experiments are conducted by using a computer mouse control instead of BCI. In the following experimental trials, the user related delay is minimized due to low delay time of the mouse, which yields the lowest possible TCT. These trials are the comparison reference (R) of a subject's performance in terms of TCT, and given at the first rows of the result tables.

Closeness (CLS(%)) is the measurement of how a subject's timing is close to the reference (R) timing in a given experiment. It is calculated using Eq.(1), where  $TCT_{s,e}$  is the TCT for a given subject,  $s$  for the experiment,  $e$ .  $TCT_{R,e}$  is the TCT for the reference R for the corresponding experiment,  $e$ .


 Figure 7: Motion trajectories and corresponding trajectory errors for  $S_1$  in experiment 2.

$$CLS(s,e) = 1 - \frac{TCT_{s,e} - TCT_{R,e}}{TCT_{R,e}}. \quad (1)$$

From the experiment results, it can be seen that majority of the subjects completed wheelchair navigation tasks over 80% closeness, except  $S_{12}$  in the first experiment (Table 1),  $S_5, S_8$  in the second experiment (Table 2, top block), and  $S_4, S_8, S_9$  in the third experiment (Table 2, bottom block). It is noted that  $S_1$  and  $S_6$  both have consistency in having high closeness ratios with small fluctuations over experiments. It is due to the fact that both of them have experience in using the NextMind device, and hence the environmental factors (distractions) have less influence on them compared to the other subjects. Another important observation from the results is regarding the device interaction tasks for inexperienced users (in the second and third experiments). A huge improvement on TCT (eventually closeness percentage) is observed from the second interaction task (coffee machine) to the third interaction task (television), even though the television control task is more complicated than coffee machine control task. The reason behind this can be attributed to the fact that each subject becomes more trained on the smart home environment by the time they perform the television control task. These observations prove that an inexperienced subject can complete the given task with high closeness value, with a very limited amount of training on the presented environment.

### 3.2 Task Commanding Success

While a subject is conducting one of the experiment's trial, he/she should follow the predefined focus patterns to complete the task. At a given point of time, if

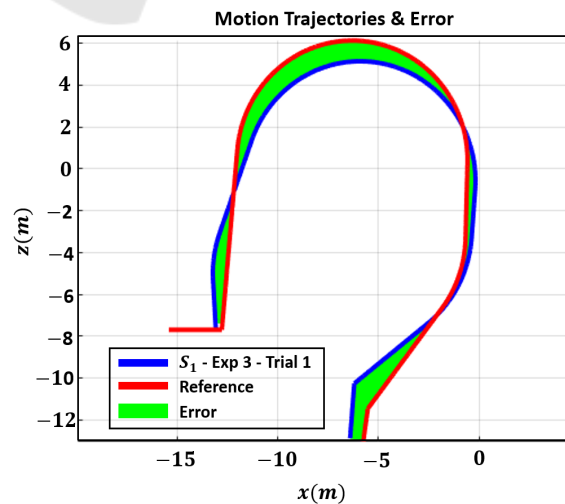

 Figure 8: Motion trajectories and corresponding trajectory errors for  $S_1$  in experiment 3.

Table 2: Experimental results for experiment 2 and 3 navigation and interaction tasks.

		TCT(s)	CLS(%)	TCS(%)	$E_{traj}(m)$	TCT(s)	CLS(%)
		Navigation			Interaction		
Experiment 2	<b>R</b>	28.1	-	-	-	15.9	-
	<b>S<sub>1</sub></b>	30.0	93.3	97.6	0.17	16.1	98.5
	<b>S<sub>2</sub></b>	30.9	89.8	93.0	0.16	17.7	88.5
	<b>S<sub>3</sub></b>	28.6	98.1	98.3	0.15	16.8	94.3
	<b>S<sub>4</sub></b>	28.9	97.2	94.1	0.17	19.9	74.3
	<b>S<sub>5</sub></b>	36.9	68.8	96.8	0.17	20.8	68.5
	<b>S<sub>6</sub></b>	32.0	86.0	97.7	0.18	17.9	86.8
	<b>S<sub>7</sub></b>	32.3	85.0	92.1	0.15	18.9	81.0
	<b>S<sub>8</sub></b>	35.5	73.6	95.2	0.18	19.2	78.9
	<b>S<sub>9</sub></b>	29.3	95.6	97.7	0.18	16.9	93.1
	<b>S<sub>10</sub></b>	28.8	97.6	98.1	0.19	18.2	85.0
	<b>S<sub>11</sub></b>	28.6	98.3	97.6	0.17	18.6	83.0
	<b>S<sub>12</sub></b>	30.5	91.5	98.5	0.22	19.1	79.3
	<b>S<sub>13</sub></b>	29.5	95.0	97.7	0.17	18.0	86.3
	<b>S<sub>14</sub></b>	28.1	99.8	92.4	0.22	17.4	90.2
<b>S<sub>15</sub></b>	30.8	90.4	98.5	0.14	17.3	90.7	
<b>Avg</b>	<b>30.7</b>	<b>90.7</b>	<b>96.4</b>	<b>0.17</b>	<b>18.2</b>	<b>85.2</b>	
Experiment 3	<b>R</b>	67.5	-	-	-	20.9	-
	<b>S<sub>1</sub></b>	72.2	93.0	94.2	0.49	21.6	96.8
	<b>S<sub>2</sub></b>	72.3	92.7	91.2	0.87	23.2	89.3
	<b>S<sub>3</sub></b>	78.1	84.2	92.7	1.12	22.6	92.1
	<b>S<sub>4</sub></b>	82.5	77.8	95.2	0.69	21.0	99.5
	<b>S<sub>5</sub></b>	77.7	84.8	95.7	1.04	21.0	99.7
	<b>S<sub>6</sub></b>	73.5	91.0	95.4	1.26	21.1	99.1
	<b>S<sub>7</sub></b>	77.1	85.6	89.5	0.74	22.5	92.4
	<b>S<sub>8</sub></b>	88.0	69.5	90.5	0.78	22.6	91.8
	<b>S<sub>9</sub></b>	85.5	73.2	95.0	1.21	21.2	98.8
	<b>S<sub>10</sub></b>	74.2	90.0	94.8	1.17	21.4	97.8
	<b>S<sub>11</sub></b>	73.4	91.2	93.4	1.26	21.3	98.5
	<b>S<sub>12</sub></b>	80.9	80.0	96.1	1.13	21.8	95.8
	<b>S<sub>13</sub></b>	75.3	88.3	93.5	1.42	21.6	97.0
	<b>S<sub>14</sub></b>	77.5	85.2	94.2	1.20	21.4	97.8
<b>S<sub>15</sub></b>	80.1	81.2	96.9	1.10	21.9	95.2	
<b>Avg</b>	<b>77.9</b>	<b>84.5</b>	<b>93.9</b>	<b>1.03</b>	<b>21.7</b>	<b>96.1</b>	

the subject focuses on a control pattern other than the required one, commanding error occurs, which can be computed as the TCS (Eq.(2)).  $C_{fail}(t)$  in Eq.(2) is the command error function. The  $C_{fail}(t)$  value is 1 if the focused pattern is different than the expected one, otherwise, it is 0 at a given time,  $t$ .  $T$  is the total time when the wheelchair in motion for a navigation task.

$$TCS = 1 - \frac{1}{T} \int_0^T C_{fail}(t) dt. \quad (2)$$

TCS for navigation tasks (on each experiment) of all subjects is over 90%. As expected, the performance of each subject decreases as the complexity level of navigation task increases. When the number of commands is increased, the probability of performing wrong navigation action is increased (Table 1 and

2). Surprisingly, none of the subjects failed on any of the interaction tasks, which yields a 100% success rate. Thus, the result indicates that the developed BCI controlled smart home application can be used by disabled users to interact with the devices with high trust level.

### 3.3 Trajectory Error

The wheelchair navigation tasks have predefined motion paths which must be followed. While subject navigates the wheelchair, its positions are recorded. Trajectory error ( $E_{traj}$ ) corresponds to the average distance error over time to the expected motion path. It shows the subject performance on driving wheelchair in terms of geometric distance (see

$E_{traj}(m)$  in Tables 1 and 2). It is calculated as shown in Eq.(3), where  $U(t)$  is the wheelchair actual position function over time, and  $R_{cp}(U(t))$  is a function that determines the closest position on reference trajectory from wheelchair position (see Figures 7 and 8). In Eq.(3),  $T$  is the total amount of time while the wheelchair is performing the navigation tasks.

$$E_{traj} = \frac{1}{T} \int_0^T |U(t) - R_{cp}(U(t))| dt. \quad (3)$$

According to the results, subjects' average navigation trajectory errors for experiments 1 and 2 are quite low (less than 20cm). However, in the third experiment, the error values increase considerably due to the complexity of the navigation path. The obtained error values confirm that all the subjects are able to navigate wheelchair on the allocated motion path with an average error of less than the width of a typical wheelchair.

## 4 CONCLUSION

In this paper, a SSVEP-BCI controlled smart home and wheelchair application developed in Unity 3D Game and Simulation Engine is presented. The system has advantage of being low-cost, wireless, portable, easy to use, and most importantly has high control accuracy without extensive training requirement. Experiments conducted on 15 control subjects show that all could complete the presented tasks with high success rates. It is also observed that the subjects' confidence and competence to control the system increases after each trial, even within the limited time of experimental proceedings. Moreover, the results clearly show that our system is considerably easy to adapt and learn by users. Preliminary testing on subjects in the virtual environment shows promising results, which supports the feasibility of the system for real-time device control applications in future smart homes.

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