SSVEP-BASED BCI PERFORMANCE IN CHILDREN

BY

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THESIS

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ABSTRACT

The first contribution of this thesis is to show that children (9-11 years old) can achieve good performance when using a Brain-Computer Interface (BCI) based on the steady-state visually evoked potential (SSVEP). In our study, ten children (mean 9.9 years old) used an SSVEP-based BCI with a mean accuracy rate of 85.6% and a task completion rate of 97.5%. In contrast, a prior study of children (mean 9.8 years old) using an SSVEP-based BCI reported mean accuracy rates of between 50%-76% (depending on stimulation frequency) and a task completion rate of 59%.

The second contribution of this thesis is to provide evidence that factors such as motivation or distraction may influence performance by children using SSVEP-based BCI more than the choice of stimulation frequency. Frequencies used by both our study (6-10Hz) and the prior study (7-11Hz) were similar. In contrast, our study asked children to play a computer game in a quiet environment, while the prior study asked children to perform text entry in a noisy environment. The game, which we developed and used for the first time in our study, is "Brain Storm" — it allows a single player to pretend to be a farmer protecting crops from malicious lightning clouds using the power of his or her brain. All participants in our study were asked both to complete a target selection task and to play the game. Our results show participants perform better when playing the game (88.6% accuracy rate) than when completing the target selection task (82.5% accuracy rate). Performance in both conditions was better than reported in the prior study (approximately 50% accuracy rate with the 7-11Hz frequency range).

To my husband, for his love and support.

ACKNOWLEDGMENTS

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CHAPTER 1

INTRODUCTION

Although Brain-Computer Interface (BCI) applications have been widely studied for adult users, not many studies have been conducted involving children. Research has recognized beneficial BCI applications for children, such as in assistive technology. However, the extent to which a child can use a BCI remains unclear. Current research aims to answer this question by conducting BCI demographic studies.

1.1 What is a BCI?

A Brain-Computer Interface (BCI) is an interface that translates signals from the brain into input for a system. The process of recording and translating brain signals dates back to 1929 when Hans Berger demonstrated he could measure the brain's electrical activity using an electrode placed on the scalp [1]. This measurement of electrical activity is called electroencephalogram (EEG). In modern work, EEG is frequently used in clinical settings as a diagnostic tool, such as for early-onset dementia [2] or for depression [3]. Monitoring brain activity through EEG has also been used in the practice of translating thoughts into actions to create a Brain-Computer Interface (BCI).

Brain-Computer Interface paradigms are well established techniques using the classification of neural activity as an input mechanisms in a system. EEG allows BCI researchers to use a variety of brain signals. BCIs have been developed using the steady-state visually evoked potential (response to flickering stimuli), the P300 response (neural response to infrequent stimuli), motor imagery (imagined left/right movements) and many more [4]. The BCI paradigm based on the steady-state visually evoked potential (SSVEP) is one of the most popular. For this research we will use the steady-state visually evoked potential.

1.1.1 Steady-State Visually Evoked Potential

The steady-state visually evoked potential is the brain's natural response to visual stimulation at specific frequencies between 1-100Hz [5]. This response was discovered in 1966 when Regan experimented with long stimulus trains of modulated light [6]. A stable response visually evoked potential was found and extracted by averaging over multiple trials.

EEG provides a fitting recording technique for SSVEP due to the good time-resolution which helps to resolve the frequency response. The SSVEP is believed to be generated through the occipital areas of the cortex [7]. Thus, researchers studying SSVEP through EEG generally place electrodes on the back of the head.

When a user focuses their attention on a flickering stimulus, the user's neural activity changes in response to the attended target. The change can be detected through EEG. When the user directs their spatial attention to the flickering stimulus, it induces an increase in EEG activity at the same frequency as that stimulus [8]. Because this phenomenon is dependent on spatial attention, this allows the user to select one target stimulus from a set of targets. BCI researchers take advantage of this fact by treating an SSVEP-stimulus as a button. The user "clicks" the button by moving their attentional focus to their desired target.

One advantage of an SSVEP-based BCI is that the application can have multiple targets, or buttons. SSVEP stimuli can be easily integrated into a variety of interfaces as it only requires that the target flickers. SSVEP-based BCIs have been gaining popularity because of their relatively high information transfer rates and the fact that they require little to no training [9].

1.2 BCI Applications & Challenges

For this overview we will briefly look at BCI for all users (clinical and non-clinical). The majority of BCI research has been dedicated to demonstrating BCI as a viable input mechanism for populations with severely impaired motor output [10], such as amyotrophic lateral sclerosis (ALS) or locked-in patients [11, 12, 13]. In these clinical populations, BCI represents a promising mechanism for communication via text entry. These BCI systems are often called "spellers". BCI spellers do not require motor input which makes them an attractive option for clinical populations. BCI spellers have been able to reach average performances of up to 11.93 cpm [12]. Researchers have explored other applications for BCIs as assistive technology. For example, BCIs have been used in systems to give users control over common home settings, such as light switches and doors [14]. These systems represent a promising application for users who would otherwise be unable to operate these common home settings by themselves.

Recently BCIs have been developed for a wide range of applications targeted at healthy users, such as computer games [15], controlling virtual vehicles [16] and even to control a robot while playing checkers [17]. This body of research helps move BCI from assistive technology to an input modality for a mass population. However, the inherently noisy nature of EEG has led to the perception that the performance of non-invasive BCIs is too low to be a viable input mechanism for healthy users [18, 19]. This presents the challenge of showing BCI as a competitive input mechanism.

The BCI field also faces the challenge of the developing of affordable, usable, commercialized hardware [20]. EEG equipment is expensive and bulky. Companies such as Emotiv [21] and NeuroSky [22] are working to create affordable, attractive BCI headsets. Still, these headsets do not perform to the level of medical systems [23].

Another challenge in BCI research is the substantial inter-subject variability in performance. This has encouraged the practice of customizing BCI parameters for each user [24]. The term "BCI illiteracy" has been used to refer to those users who are unable to attain effective control of the BCI application. Approximately 10%-20% of users fall into the "BCI illiteracy" phenomenon [24]. This phenomenon has led to an increase in BCI research that explores demographics through various methods, tasks, and applications [24, 25]. Although these types of demographic studies examine factors such as age and gender in relation to BCI performance, they generally only consider users over the age of 18. In fact, the number of studies involving children remains very small [2].

In a recent review, Mikotajewski emphasizes the importance of BCI research involving children [2]. Mikotajewski argues that BCIs could be useful as diagnostic or rehabilitation tool for children with neurological disorders. For example, [26] showed BCI as a training tool for children with attention deficit hyperactivity disorder. In addition, there is an increasing number of BCIs designed for entertainment which children may enjoy. Children represent a large possible target group of BCI users. Children are a major consumer group of many forms of technology. It has been estimated that children between the ages of 8-10 years old spend an average of 5 hours a day using some form of media, roughly 3.5 hours a day watching TV, and use some form of a device with a screen every day [27]. As BCI moves forward towards becoming commercialized, it is likely children will be interested in these devices.

This study seeks to contribute to the field of BCI demographic research by looking at BCI performance in children (ages 9 to 11). The remainder of this report will be organized into the following chapters: Chapter 2 will provide a literature review to present the results of related works and to motivate this study. Chapter 3 will detail the experimental procedures used in this work. Chapter 4 will present the results of the study. Finally, Chapter 5 discusses the implications of the results in context with the related works and areas of future research.

CHAPTER 2

RELATED WORK

Prior BCI demographic research has found performance to be influenced by age. Specifically, children and older adults have been shown to not perform as well as young adults. The causes driving these age group distinctions is not clear and further research is needed to fully understand the extent of these performance differences. Our work builds on this age-driven research by looking at SSVEP-based BCI performance in children.

This chapter presents a literature review of some of the related work used to motivate our research. These works contribute to a body of research dedicated to uncovering the causes of poor BCI performance in both adults and children. Each section in this chapter will give an overview of the methods and results of the related research. For this section we limit our review to non-invasive SSVEP-based BCIs.

2.1 BCI Demographics

This section reviews the work done in 2101 by Allison to examine the relationship of various parameters to SSVEP-based BCI performance [24]. Allison argues that before BCIs can become usable in everyday settings, BCI demographics must be better addressed. The large amount of inter-subject variability has led to a noticeable amount of users who are “BCI illiterate”(10% - 25% of users). Although some research has hypothesized reasons behind "BCI illiteracy", there has been little work in this area and the causes of “BCI illiteracy” still remain largely a mystery. Allison’s work considered parameters such as personal preferences, age, gender and individual characteristics.

The study was conducted at a large computer expo (CeBit 2008). 106 Participants (ages 18-79 years old, 25 female) were asked to use a BCI speller.

Subjects were asked to spell five phrases. Four of the phrases were provided by the experimenter and the fifth was selected by the subject. Brief questionnaires were administered both before and after BCI use to gather information on individual characteristics.

Subjects in this study reached a mean accuracy rate of 95.78% across all words spelled. Analysis was conducted on the relationship between mean information transfer rate (ITR) with respect to age and gender. There was no statistically significant effect found. Nor was there a significant effect found for other individual characteristics (e.g. need for glasses, amount of sleep the night before). However, while not statistically significant, younger subjects were observed to be more positive about BCI use and achieved a higher information transfer rate.

Allison notes prior work has indicated that different thresholds and stimulation frequencies are more effective for some subjects. During this study, two tactics used to minimize SSVEP-based BCI illiteracy were to change to stimulus frequency for the button used to select a character and to manually change the selection threshold. These tactics were sometimes effective, but time consuming. Based on this, Allison encourages researchers to explore several different sets of stimulation frequencies within each subject. This will help to optimize the settings for each subject and may also lead to a better understanding of what frequencies work with which subjects. In addition, while this work did not find an effect on BCI performance in relation to individual characteristics, further investigation is needed to verify these results.

2.2 BCI Performance & Stimulation Frequencies

This section describes the work conducted by Voloskay from 2011 [25] as a follow up to Allison's research in [24]. This research also approached BCI demographics by looking at subject factors and personal preferences in relation to performance. This study builds on the research in [24] by using two sets of SSVEP stimuli (medium: 13-16Hz and high: 34-40Hz frequencies). Volosyak proposes using stimulation frequencies over 30Hz as they have been found to be less annoying and can reduce user fatigue. However, one challenge with high stimulation frequencies can be a reduced amplitude in the SSVEP response. In order to explore this challenge, Volosyak compares the performance of adults using an SSVEP-based BCI with two sets of stimulation frequencies.

86 participants between the ages of 18-55 were recruited by visiting the author's booth at a fair. This setting had a high level of background noise. Participants were asked to navigate a miniature robot through a labyrinth by giving commands using four flickering LED SSVEP stimuli. Volosyak notes that the application was changed from a BCI speller to robot control in hopes of attracting more subjects. Each participant was asked to complete a short practice run to become familiar with the system. Next the participants completed two sessions in which the navigated the miniature robot out of the labyrinth (one using the medium and high SSVEP frequencies).

This study revealed a significant difference in BCI performance between the two frequency sets, with participants reaching a mean accuracy rate of 92.26% (medium frequency set) and 89.16% (high frequency set). As in [24], no effect was found with respect to gender or age. The results of this study show the importance of understanding the relationship between stimulation frequency and SSVEP-based BCI performance for the user. Researchers must carefully consider the stimulation frequencies selected for the users. In order to fully understand what frequencies work for what users more BCI analysis is required.

Another point of note, the researchers in this paper selected their BCI application to try to attract more participants. This may suggest that the type of task given (spelling or controlling a robot) may be an influence on BCI subjects not only in initial participation in a study, but may impact engagement while completing the study.

2.3 BCI Performance & Age

This section describes a 2015 study in which Gembler analyzed the effect of age on SSVEP-based BCI performance [28]. While previous studies such as [24] and [25] looked at the relationship of age on BCI performance, these studies had very few participants over the age of 50. In addition, neither study found the interaction between age and performance to be statistically significant. In this work, Gembler revisits the relationship between age and

SSVEP-based BCIs. Specifically interested in older subjects, Gembler tested the SSVEP-based BCI performance for two equally sized age group of subjects. In contrast to [24] and [25], Gembler found a significant difference in performance between the age groups.

Five subjects between the ages of 19 to 27 and five subjects between the ages of 66 to 70 completed this study. The younger group of subjects had a little or no prior BCI experience and the older group had no prior BCI experience. Participants were asked to use an SSVEP-based BCI speller to type a seven word long German phrase.

The results of this work found the younger group to perform better (mean accuracy: 97.29%) than the older group (mean accuracy: 89.12%). In addition, participants in the older group (mean 1053.31 seconds) needed noticeably more time to complete the spelling task than the younger group (mean 616.93 seconds). This difference supports further analyses of the relationship between age to SVEP-based BCI performance to understand what factors contributed to the poorer performance of the older participants. For example, one explanation might be the role of BCI experience. In this work the younger subjects had some or no BCI experience while the older subjects were all novice to BCI. The contrast of the findings between this study and those in [24] and [25] show the importance of revisiting various factors in relation to BCI performance in order to verify the results. This study also motivates further analysis of BCI performance in connection to other age groups.

2.4 Comparing BCI Performance Between Children & Adults

These SSVEP-based BCI demographic studies explored BCI demographics using different methods, tasks, and applications [24, 25, 28]. Age was shown to be an influencing factor on performance, where young participants seem to perform better and also tended to be more positive about the BCI system. Each of theses studies looked at age in relation to BCI performance, but did not include users under the age of 18. Although the SSVEP response in children has been studied ([29, 30]), very few studies have examined the performance of children using an SSVEP-based BCI application [2].

Table 2.1: This table reports the results of the study in [31]. Approximate mean accuracy by is given by age group and SSVEP stimulation frequency range.

Age Group (mean age in years)	Stimulation Frequency Range *Low* $(7-11Hz)$	*Medium* $(13-17Hz)$	*High* $(30-48Hz)$
Group 1 (6.73)	40%	58%	39%
Group 2 (8.0)	50%	50%	45%
Group 3 (9.8)	50%	76%	58%
Group 4 (22.3)	78%	78%	62%

This section reviews work by Ehlers conducted in 2012. The goal of this study to assess the extent to which development-specific changes in background EEG influence SSVEP-based BCI performance by comparing children and adults [31]. To understand BCI performance as a function of age, multiple age groups and sets of stimulation frequencies were used in this study. Participants were divided into roughly equal age groups (ranging from mean of 6.73 to 22.36 years old). SSVEP stimuli were split into three sets: low frequencies (7-11 Hz), medium frequencies (13-17 Hz), and high frequencies (30-48 Hz).

51 adults and children (6 - 33 years old) with no prior BCI experience were tested using an SSVEP-based BCI speller. The study took place in a room with a high level of background noise. Participants were asked to spell six words, two words with each frequency set. The youngest group of participants were given different words and only asked to spell one word per frequency set. Each session took around 45 minutes.

The approximate mean accuracy rates for this study are shown in Table 2.1. The results show adults consistently performed better than children. The adult group (mean 22.3 years old) achieved mean accuracy rates of approximately 78% for both the low and medium frequency condition, and approximately 62% in the high frequency condition. In contrast, the mean accuracy rates for children were generally in less than 60%, with the exception of the oldest group in the medium frequency condition (approximately 76%). There was a significant age group effect in the low frequency condition. No age effect was observed in the medium frequency condition and only a difference between the adults and the youngest group (mean 6.73 years old) was observed for the high frequency condition. All groups performed best at medium frequency. However, Ehlers points out this frequency may cause annoyance and/or fatigue and may not be the best in a real-world setting.

In addition to these results, Ehlers reported a high number of canceled tasks. Task completion rates were 21% for the youngest group, 29% the next oldest group (mean 8.0 years old), 59% for the oldest child group (mean 9.8 years old) and 62% for adults.

While Ehlers suggests poor performance rates of the children in this study was perhaps due to an inability to generate signals in the different frequency ranges, there are some other possible factors. First, this study was conducted in a noisy environment. This may have caused some level of distraction for participants which may have impacted performance. Although both [24] and [25] were conducted at fairs which might also be noisy, children may be more susceptible to distraction. In addition, the number of canceled tasks may indicate a lack of interest or engagement from the participant. Because even the adults had a low task completion rate, it is worth researching the causes behind this result.

In order to fully understand the extent to which children are able to use an SSVEP-based BCI more investigation in needed. Our work continues this analysis by focusing in on the oldest age group of children used in [31]. In addition, we vary our approach by conducting our study in a lab and asking the participants to use two different SSVEP-based BCIs. Our study is will evaluate the performance of children (9-11 years old) using an SSVEP-based BCI. Our goal is to contribute to a better understanding of the parameters that influence BCI performance for this age group. The details of our experimental methodology are given in the next chapter.

CHAPTER 3

METHODS

Our study was conducted to test the performance of children (9-11 years old) using an SSVEP-based BCI. We vary our approach from prior research by asking participants to use an SSVEP-based BCI to select a sequence of targets and play computer game while in a quiet setting.

3.1 Participants

10 able-bodied volunteers (9-11 years old, M = 9.9, SD = 0.74) were recruited to participate in this study. Subjects were recruited through email bulletins, a booth at the University of Illinois Beckman Open House, and word of mouth. Prior to participating, subjects were given an informational letter with a short description of the research. Participants recruited through the booth at the Beckman Open House had an opportunity to watch a short demonstration video of an SSVEP-based BCI. All subjects had normal or corrected-to-normal vision and no prior history of neurological illness. All of participants had no previous experience using an SSVEP-based BCI and had not previously seen the applications used in this study. Each participant was compensated for their time with a small gift (less than $5.00US). Children signed assent forms to indicate their voluntary participation. Written consent was obtained from the legal guardian of the subject. This study was approved by the Institutional Review Board at the University of Illinois at Urbana-Champaign.

3.2 EEG Recording

EEG data was recorded from the surface of the scalp through six solid tin electrodes. The electrodes were placed at sites across the occipital region of the scalp; the channels according to the international 10-5 system were P03, POZ, PO4, O1, OZ, and O2. These channels were grounded to the right ear. The channels were referenced to the top of the head (location CZ). A small amount of conductive gel developed by Electro-Cap International (specifically designed for use with EEG systems) was applied to the skin under the EEG electrodes. Signals were sampled at 256 Hz. All electrode impedances were below 10kΩ during recording. The EEG signals were amplified using a James Long bioamplifiers, bandpass-filtered from 1Hz to 30Hz, and digitized at 128Hz using a National Instruments data acquisition unit (Model PCI-6225). The open source framework BCI2000 was used to record and visualize EEG signals. An example of the raw EEG data collected during the study can be seen in Figure 3.1.

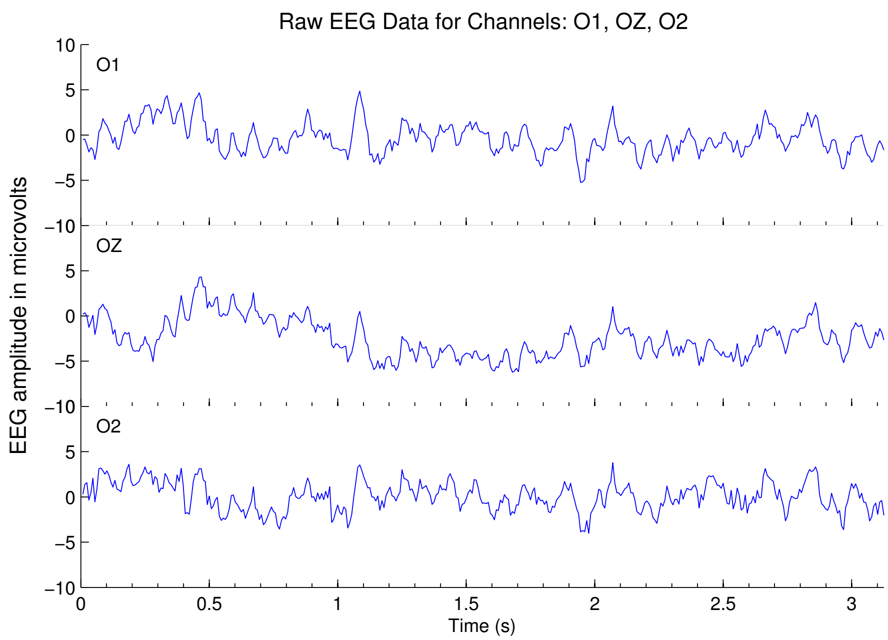


Figure 3.1: A visualization of raw EEG data for channels O1, OZ, and O2.

3.3 Experimental Procedures

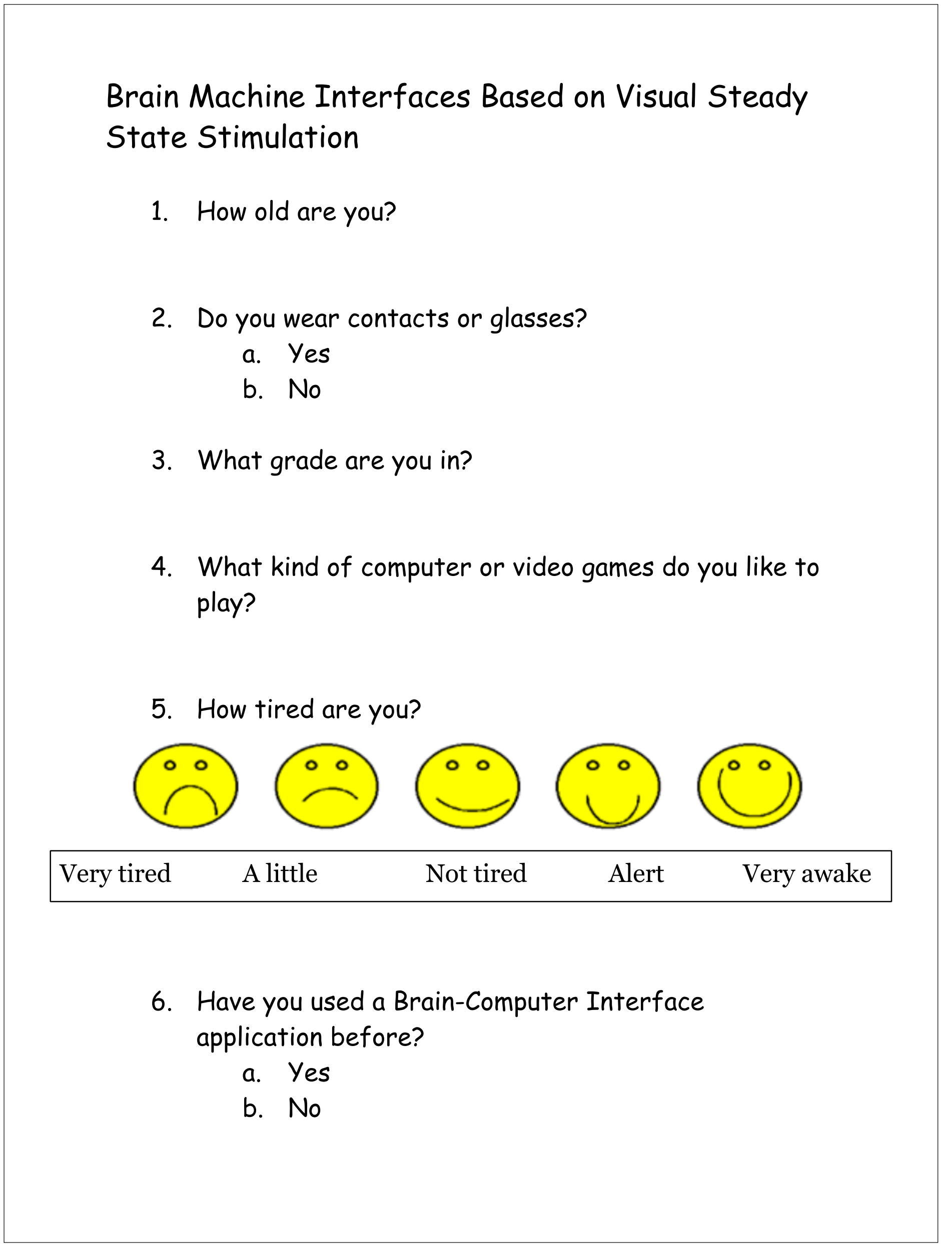
On arrival, participants and guardians were given a brief tour of the lab and overview of the research. The child participants were read an information sheet and asked to write their name if they consented to the study.

A guardian of the participant was given an information sheet and asked to provide written consent. Both the child and guardian were given the opportunity to ask the researcher any questions they had. After completing the consent process, each subject was asked to complete a brief survey with basic background questions, based on the questionnaire used by [24] and using scales designed for children surveys by [32]. The survey is shown in Figure 3.2.

Experimental sessions were conducted in a cool and sound attenuated room with dim ambient lighting. The participants were seated in a comfortable office chair between two speakers facing an LED computer monitor (24-inch BenQ XL2420T). Guardians were given an option to sit in the experiment room with the participant or in an adjacent room. In some cases the participant's siblings accompanied them to the study. In this case we asked that the siblings sit in the adjacent room to minimize distraction for the participant. In all experiments participants were asked to focus their visual attention on a stimulus blinking at a prespecified rate. The steady-state stimuli were three targets presented on the monitor at 6.25, 8, and 10Hz. The stimuli appeared as either ovals or clouds flickering between white and black. When the user was presented with SSVEP stimuli, EEG signals were recorded to be used in determining where (on which stimuli) the user was focusing their attention.

After finishing the survey, each subject completed a training phase. The resulting data was used to set the parameters for the accuracy and latency model for the user. Following training, participants were asked to complete two-part application phase. The purpose of this phase was to evaluate any effect that type of application may have on performance. In addition, the goal of this phase was to see if any additional factors, such as motivation, may be influencing performance.

We created a simple application for completing a target selection task. The goal of the application is to select a sequence of targets using SSVEP. This will be referred to as the "control condition". In this condition, the user is asked to select a sequence of targets as shown in the interface in Figure 3.4 and is explained in more detail below. We also created a computer game based on the target selection task. This game, which we developed and used for the first time, is called "Brain Storm" (Figure 3.5). The game phase of the study will be referred to as the "test condition". The test condition is described in greater detail below.



Brain Machine Interfaces Based on Visual Steady State Stimulation

1. How old are you?

2. Do you wear contacts or glasses?
   a. Yes
   b. No

3. What grade are you in?

4. What kind of computer or video games do you like to play?

5. How tired are you?

Very tired	A little	Not tired	Alert	Very awake

6. Have you used a Brain-Computer Interface application before?
   a. Yes
   b. No

Figure 3.2: An example of the pre-study questionnaire administered to participants.

In both conditions the participant was asked to select a sequence of 15 targets in four rounds (for a total of 60 targets per condition). The order of the specified target was randomized. Each of the three possible frequencies is specified as the target five times per round (for a total of 20 times per condition). In each condition, after completing the four rounds the application enters into a fifth, free-play. In this round the participant can use the application as long as they would like (up to 10 minutes). The order of conditions was randomized to reduce ordering effects. The entire study took on average one hour.

3.3.1 Training Phase

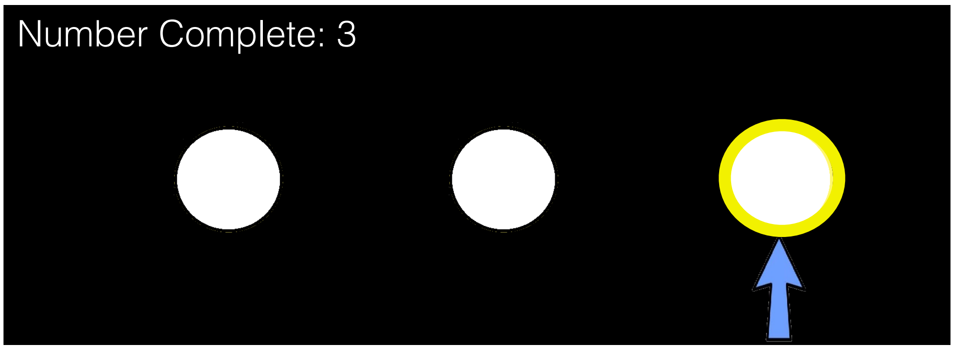
Each participant completed a short training phase to calibrate the system and to find a signal to noise threshold to be used in the experimental session. During the control and test condition, if the signal to noise ratio of a specific frequency exceeded a certain threshold, the corresponding target is selected. For example, if activity at 10 Hz exceeds the threshold, the target flickering at 10 Hz is selected. Data from the training phase was used to set this threshold. In order to increase accuracy, a minimum window length of 1.25 seconds was set before the system would make any classification.

In the training phase, participants were asked to attend to a sequence of 15 targets. The participants were given instructions on the training and allowed to start the application when they were ready by pressing a key on the keyboard. The splash screen of the training included a place for the participant's initials, or favorite number to be displayed (Figure 3.3a). This information was not saved and was used to allow for some personalizing in the interface. Once the application was started, an arrow specified the intended target for each trial (Figure 3.3b). Participants were instructed to attend to that target by focusing their attention at the stimuli. Each trial lasted five seconds, with a short pause between trials. The order of the specified targets was randomized with each of the three frequencies specified as the intended target five times. The training phase took no more than five minutes.

3.3.2 Control Condition

In the control condition, users were asked to select a sequence of targets using our SSVEP-based BCI. The splash screen for the control condition was similar to the training interface (Figure 3.4a). Participants were allowed to provide their initials, or a number to personalize the screen. This was not

(a)



(b)

Figure 3.3: This is a sample screen shot of the training interface. The targets flicker between white and black. (a) Shows a sample of the splash screen. (b) Shows a sample of the main training interface. The arrow under the highlighted target indicates the participant show focus their attention on this target.

saved after the application was closed. The researcher provided instructions on how to use the application and when the participant was ready they pressed a key on the keyboard to begin.

The interface displayed three targets. The target highlighted in yellow indicated that the user should select this target (Figure 3.4b). The top of the interface displayed the number of trials completed. Participants selected targets using SSVEP by shifting their attentional focus. A check mark was placed in the location the selected target (Figure 3.4c). Each trial lasted 5 seconds, or until a selection was made. A short tone was played when a selection has been made. The application paused for 1 second between trials. Between rounds the application played a short tone and paused for 6 seconds. A message was displayed indicating the end of the round (Figure 3.4d). At the end of the session a short message was displayed to the user letting them know the session was completed (Figure 3.4e).

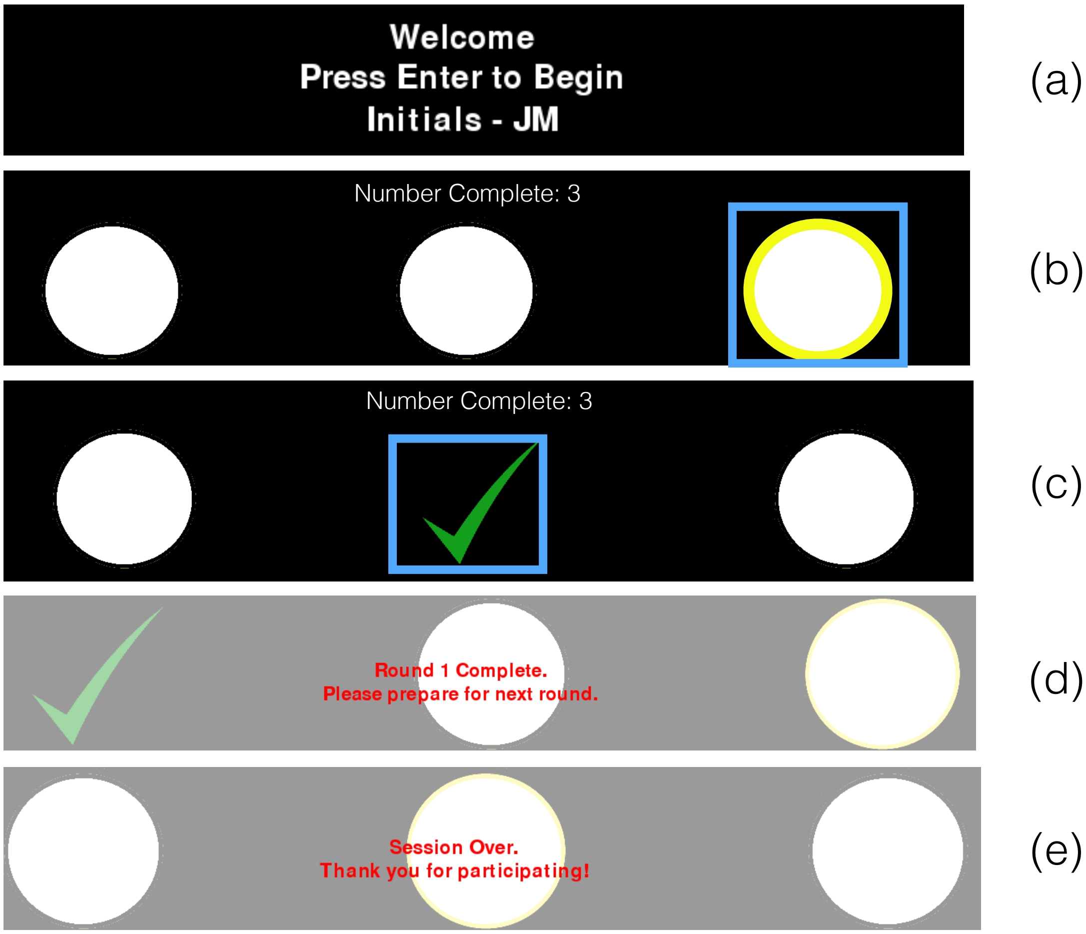
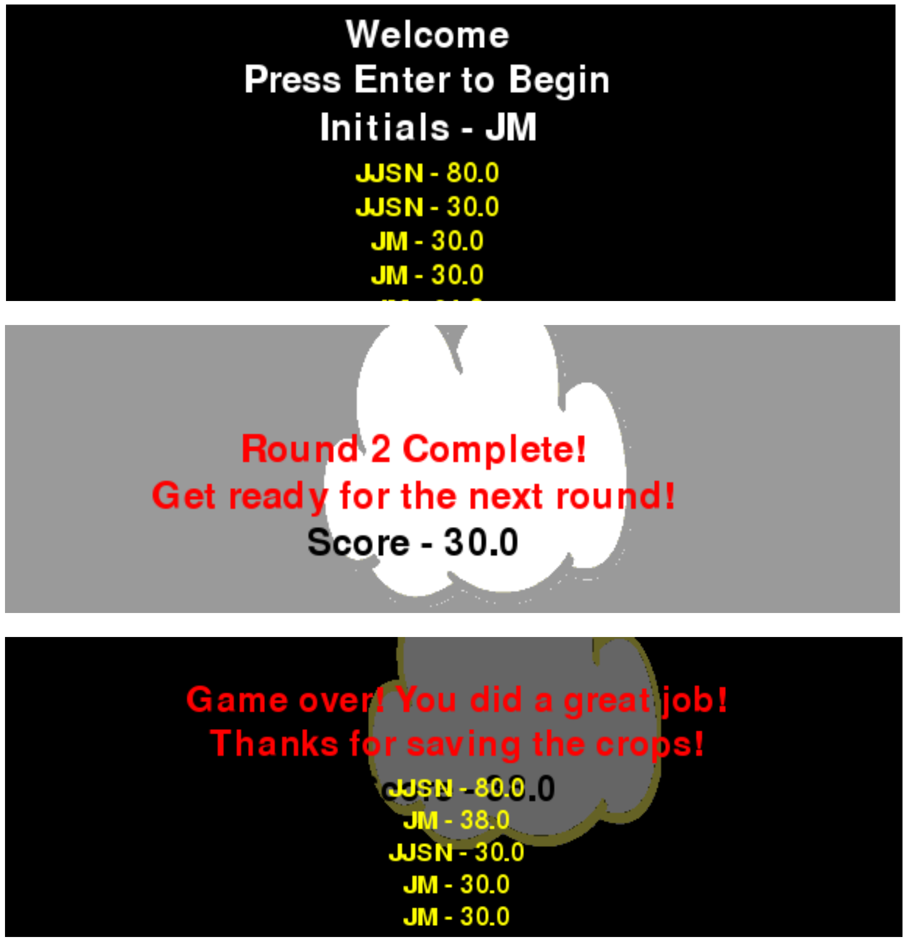


Figure 3.4: A sample screen shot of the splash screen for the application in the control condition. The targets flickers between white and black. (a) Shows a sample of the splash screen for the application. (b) Shows a sample of the main application interface. The target the user should attend to is highlighted with a yellow circle. (c) Feedback is given to the user when one of the targets is selected. A check mark is placed in the location of the selected target. (d) Shows a sample screen shot of the application between rounds. (d) Shows a sample screen shot of the interface at the end of the session.

3.3.3 Brain Storm

In the test condition game elements were added to the control interface to create "Brain Storm". Game play for Brain Storm followed the target selection task in the control condition. Users were asked to select a sequence of targets using our SSVEP-based BCI. The test condition consisted of four rounds with 15 trials. Just as in the control condition, each of the three frequencies was specified as the intended target five times per round. One



(a)

(b)

(c)

Figure 3.5: Sample screen shots of the splash screen (a), screen between game rounds (b), and final game screen (c) for the test interface.

modification added to the application was changing the "free play" round to a "bonus round". Users were told if they successfully made it to the bonus round they could play the game as long as they would like (up to ten minutes). The only requirement to make it to the "bonus round" was to complete the first four rounds.

Another modification was the addition of a scoring system to the application. For each target correctly selected, the user received points. The score appeared in the top of the screen, similar to popular video games. A 'high score' screen was added as part of the scoring system. Prior to the game starting, the user was presented with a list of 'high scores' (Figure 3.5a). This list was artificially populated by the researchers and was created to serve as a motivational goal. Users were shown their scores between rounds (Figure 3.5b). At the end of the game the user was presented with the high score list again to see where they ranked (Figure 3.5c).

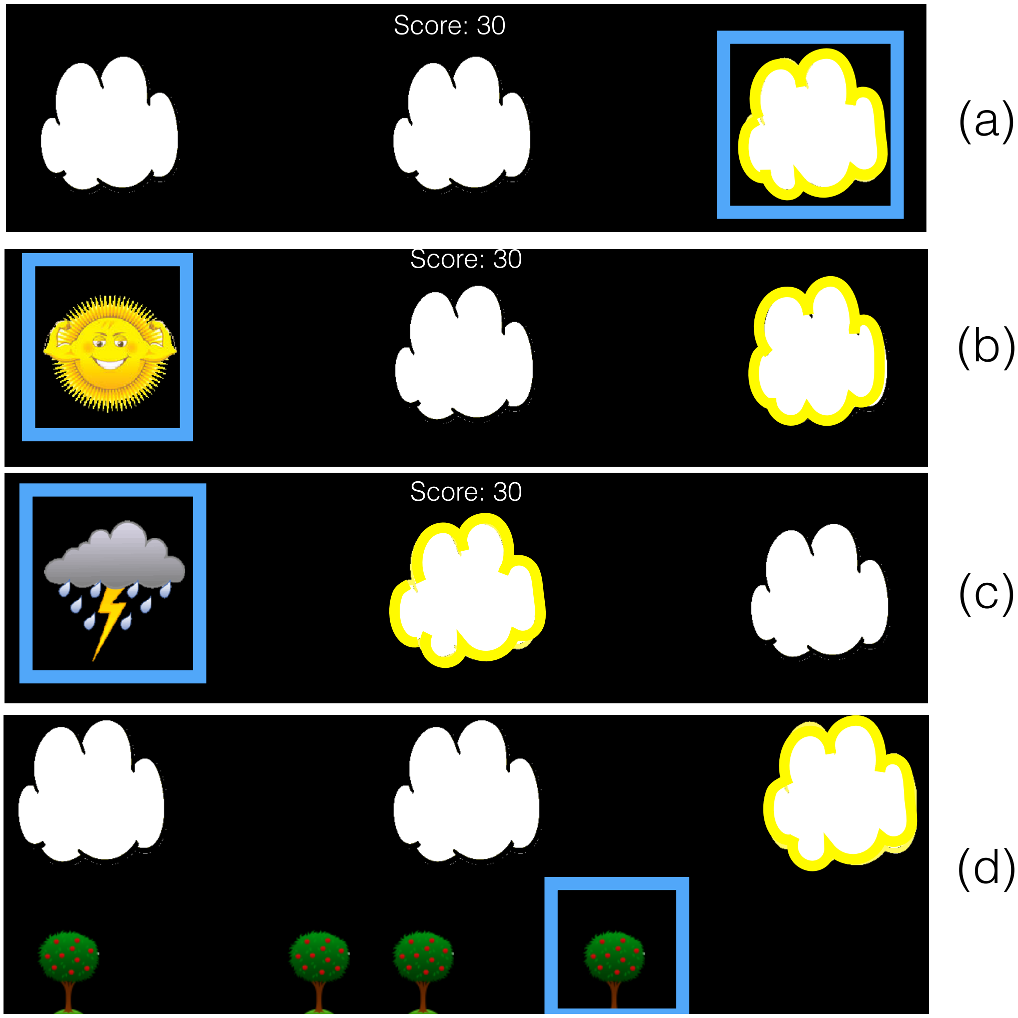


Figure 3.6: Sample screen shots of the main game interface. (a) Shows the three targets. One target is highlighted in a yellow outline indicating that the user should select this target. (b) Shows the feedback given to the user for a correct target selection. (c) Shows the feedback given to the user when selecting a target without a yellow highlight. (d) When the user correctly selects a target, they gain crops which are added to the bottom of the screen.

A small story line was added to the game. Users were told that "they are a farmer who must help their crops grow by protecting them from the dangerous thunderclouds". The participants were told that they would be presented with three clouds, and one would be highlighted in yellow indicating it is a dangerous thundercloud (Figure 3.6a). To protect the crops, the farmer must use the power of their brain to destroy the cloud with the sun (Figure 3.6b). When a user successfully protects their crops from the dangerous thunderclouds, more crops grow (Figure 3.6d). For each thundercloud destroyed, a new crop would appear at the bottom of the screen. If the user destroyed a non-threatening cloud, the cloud was turned into a thundercloud (Figure 3.6c). No other penalty was given for destroying a non-threatening cloud.

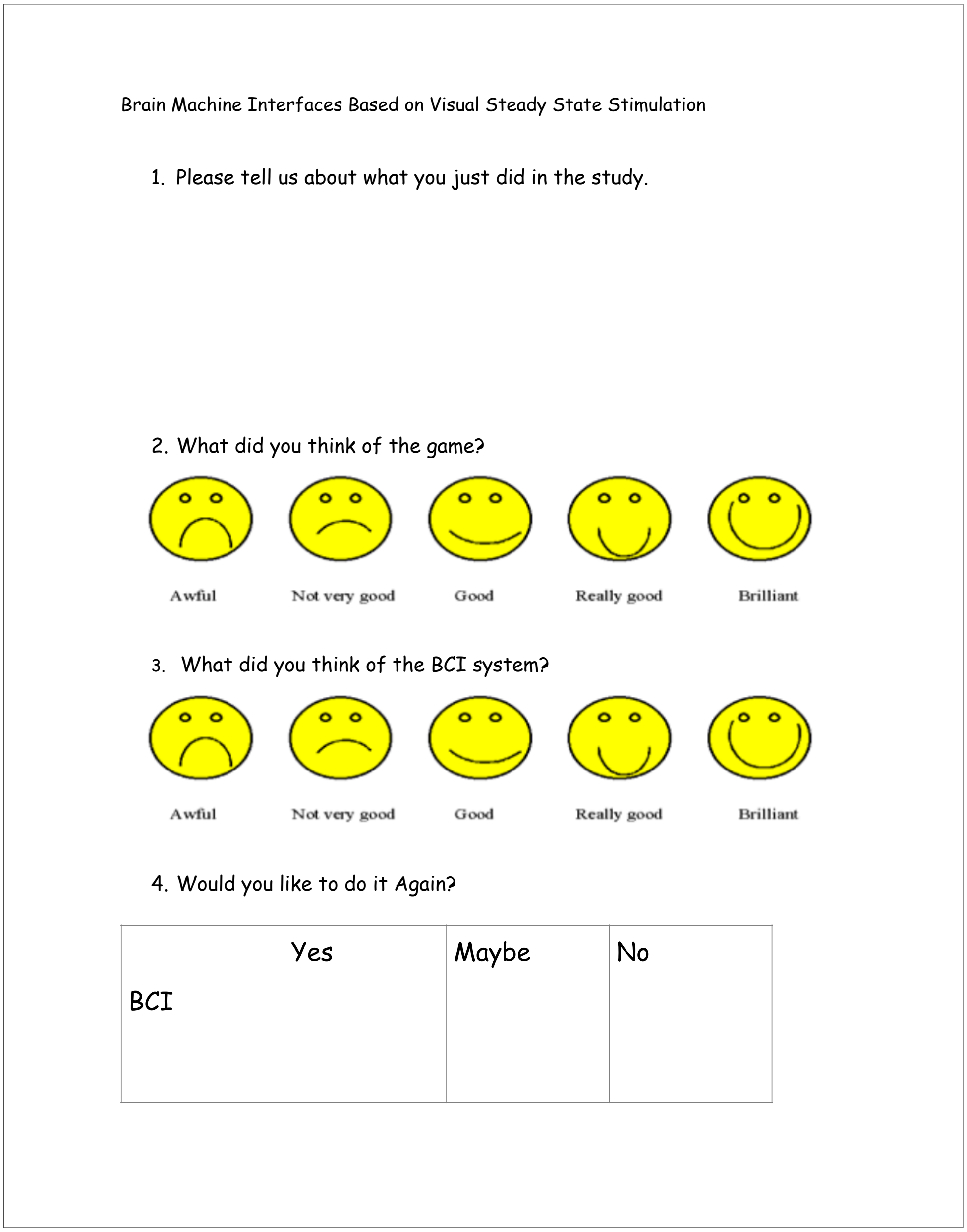
The graphics and sounds in the interface were modified from the control condition. The white ovals were changed to white clouds. Plants were added along the bottom of the screen to increase the feeling of protecting crops. Instead of a check mark indicating a selected target, the user was presented with a powerful sun graphic (Figure 3.5b) for a correct selection along with an uplifting sound effect. If a target was selected that was not highlighted the user was presented with a thundercloud (Figure 3.5c) and thunder sound effect. At the end of each round a fun melody was played as a transition.

All participants were told at the start of the study they would be compensated with a small gift. In the test condition the participants could win the ability to select their gift out of five options. Before starting the test condition, participants were given time to rank five prizes from most (5) to least (1) desirable as done in [33]. For each round completed, the participant could select a prize corresponding to the ranking and below. For example, if the participant completed three rounds they could select from third ranked prize and down. If the participant made it to the bonus round they could select any of the prizes. Each prize was no more than $5.00US. The prizes were items such as bubbles, bouncey balls, paint sets, and small stuffed animals. Participants were compensated with a prize even if they chose not to participate in the game phase.

3.3.4 Engagement Metrics

Following both the test and control condition, participants were asked to complete a brief survey (Figure 3.7). The open response question encouraged the participant to reflect on what they had just done. The remaining survey questions were developed using both the Smileyometer and Again-Again table developed by [32]. These questions gave the participants an opportunity to provide feedback on the application and the BCI system. The Again-Again table was used to measure their engagement with the system. The survey was administered after both the control and test condition to measure engagement for both conditions. The surveys also were used to be able to compare the opinions on both interfaces and to see if the participant's opinion of the BCI system changed between conditions.

Previous work with children has noted that children often request to end trials or studies early [31, 33]. Task completion rates have been used to measure engagement [33]. We define task completion rates to be the percentage of trials completed for both conditions. For the task completion rates we consider the first four rounds separate from the fifth round. The fifth round was used as a free play round and therefore each participant completed a different number of trials. We use time spent in the fifth round as an additional metric to measure engagement. This metric was modeled after Malone's use of time spent using an application to gauge how much a participant liked using it [34]. Participants were given the opportunity to use both the control and test application for as long as they liked (up to ten minutes). The amount of time spent, and number of trials completed, using the application and number of trials was recorded as a metric of engagement.



Brain Machine Interfaces Based on Visual Steady State Stimulation

1. Please tell us about what you just did in the study.

2. What did you think of the game?

Awful Not very good Good Really good Brilliant

3. What did you think of the BCI system?

Awful Not very good Good Really good Brilliant

4. Would you like to do it Again?

	Yes	Maybe	No
BCI			

Figure 3.7: Post-study survey given to participants after completing both the control session and the test session.

CHAPTER 4

RESULTS

A total of 10 participants completed our study. The participants reached a mean accuracy rate of 85.6% across all trials. Our results show a high mean task completion rate of 97.5% for all participants. This result demonstrates that children were able to achieve good performance when using our SSVEP-based BCI. Mean accuracy rates in the test condition were 88.6% compared to 82.5% in the control condition. This result provides evidence that factors such as motivation may contribute to performance. Overall, the results of this study are encouraging and provide motivation for future BCI studies with children.

4.1 Accuracy

Accuracy is defined as the total number of correct target selections divided by the total number of targets presented. A correct target selection is defined as one where classification was made on the highlighted target. As mentioned in the previous section, if the signal to noise ratio of a specific frequency exceeded a certain threshold, the corresponding target was selected. Figure 4.1 shows the mean accuracy across as a function of window length across all participants, with no threshold. We can see from this graph that accuracy only reaches just below 90% after five seconds. In order to get to 100% accuracy, different thresholds were set depending on the participant performance in the training session. Figure 4.2 shows the difference in accuracy as a function of window length with and without a threshold for a single subject. We can see for this subject, by setting a threshold of 0.70 we are able to reach 100% accuracy after about two seconds.

In the control and test condition, mean accuracy across all subjects for all trials was 85.6%. This result shows that for most participants, our SSVEP-

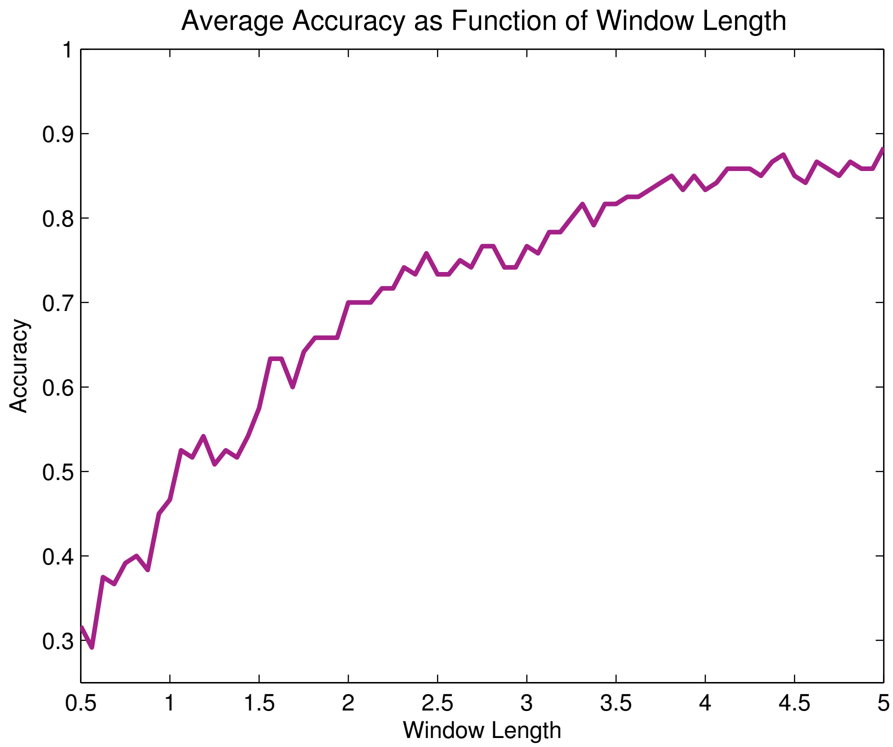


Figure 4.1: This graph shows mean accuracy as a function of window length.

based BCI could be used with effective accuracy rates. In fact, all participants (except S07) were able to achieve at least 77% accuracy. A break down of each participants' accuracy across rounds is shown in Table 4.1 and Table 4.2. Table 4.3 shows the overall mean accuracy for the control and test condition for each participant.

Participants in the test condition reached (M:88.6%) higher mean accuracy rates (t(9)=1.87, p=0.094) than those in the control condition (M: 82.5%) (Figure 4.3). Although this result is not quite statistically significant, it is consistent with our expectations. Figure 4.4 shows the mean accuracy across all subjects for each round of the application in both sessions. This result shows that in all rounds, except round one, mean accuracy was consistently higher in the test condition.

Figures 4.5, 4.6 and 4.7 give a confusion matrix representation of the instances of classification across all participants. The classes (6.25Hz, 8Hz, and 10Hz) represent each of the stimulation frequencies. The NULL column represents when no classification was made. Although no large trend is ap-

Table 4.1: Mean accuracy by subject, for each round in the control condition. Blank values indicate that the subject completed no trials for that round.

	Round				
Subject	1	2	3	4	5
S01	0.93	0.93	0.93	1.00	0.95
S02	0.93	1.00	0.93	0.80	0.61
S03	0.80	0.86	0.86	0.73	0.73
S04	1.00	0.73	0.86	0.86	0.73
S05	0.86	0.73	0.86	0.93	0.76
S06	0.93	0.93	0.80	0.80	0.80
S07	0.60	0.60	0.66	0.60	0.66
S08	0.93	0.93	0.60	1.00	0.96
S09	1.0	0.66	0.86	0.93	
S10	0.86	0.93	0.93	0.93	0.80

Table 4.2: Mean accuracy by subject, for each round in the test condition. Blank values indicate that the subject completed no trials for that round.

	Round				
Subject	1	2	3	4	5
S01	0.53	0.86	0.80	0.86	1.00
S02	1.00	1.00	0.86	0.86	1.00
S03	0.86	0.86	0.73	0.80	0.80
S04	1.00	1.00	1.00	0.93	0.85
S05	0.73	1.00	0.93	0.93	0.89
S06	0.93	1.00	0.93	0.93	0.85
S07	0.60	0.46	0.40	0.80	
S08	1.00	0.93	1.00		
S09	0.93	1.00	1.00	0.93	0.84
S10	1.0	0.93	1.0	1.0	1.0

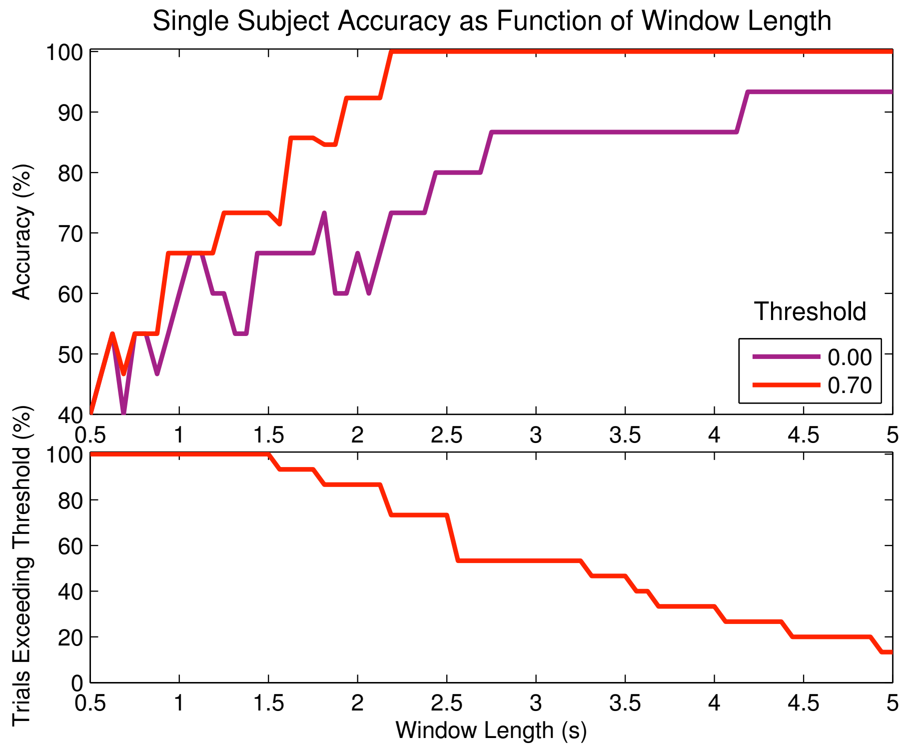


Figure 4.2: This graph shows accuracy as a function of window length for a single subject. With no threshold set, accuracy does not reach 100%. When a threshold of 0.70 is set, accuracy reaches 100% after about 2 seconds.

parent in Figure 4.5, we found participants generally performed better with the 8Hz and 10Hz class. Figure 4.6 shows the difference between the test and control class. From this figure we can see that the test condition may help participant's performance with the 6.25Hz stimulus.

4.2 Latency

We define latency as the time it takes to obtain a user response after the onset of a stimulus. Note, a window length of 1.25 seconds was set before the classifier would make any selection. This was set to try to increase accuracy rates. Mean latency across all trials for all subjects was 2.36s. Table 4.4 and Table 4.5 show the mean latency by round for each participant.

The mean latency for the control (M=2.32s) and test (M=2.40s) conditions were very similar and had no significant difference ($t(9)=0.55$, $p=0.59$) (Figure 4.8). Figure 4.9 shows the mean latency across all subjects for each

Table 4.3: The overall mean accuracy for each subject for both conditions.

	Control	Test
S01	0.95	0.82
S02	0.77	0.94
S03	0.80	0.81
S04	0.78	0.92
S05	0.83	0.89
S06	0.86	0.92
S07	0.62	0.56
S08	0.90	0.97
S09	0.85	0.92
S10	0.89	0.98

Table 4.4: Mean latency by subject, for each round in the control condition. Blank values indicate that the subject completed no trials for that round. Time is in seconds.

	Round				
Subject	1	2	3	4	5
S01	1.59	1.51	1.52	1.58	1.56
S02	1.89	2.03	2.57	2.18	2.52
S03	2.02	2.42	2.48	2.09	1.95
S04	3.14	3.10	2.81	2.83	3.07
S05	2.35	2.00	2.25	2.07	1.86
S06	2.29	2.39	2.41	2.38	2.13
S07	2.02	2.07	2.04	2.03	1.99
S08	1.42	1.41	1.37	1.38	1.42
S09	3.87	3.57	3.91	3.89	3.92
S10	2.08	2.02	1.94	2.22	2.19

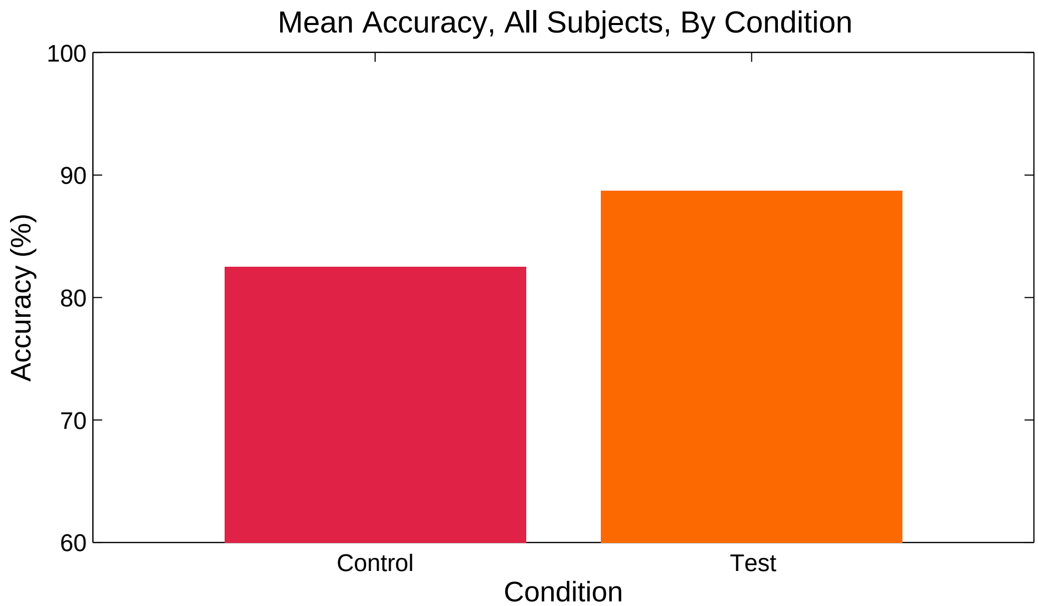


Figure 4.3: The mean accuracy across all subjects by condition for all rounds.

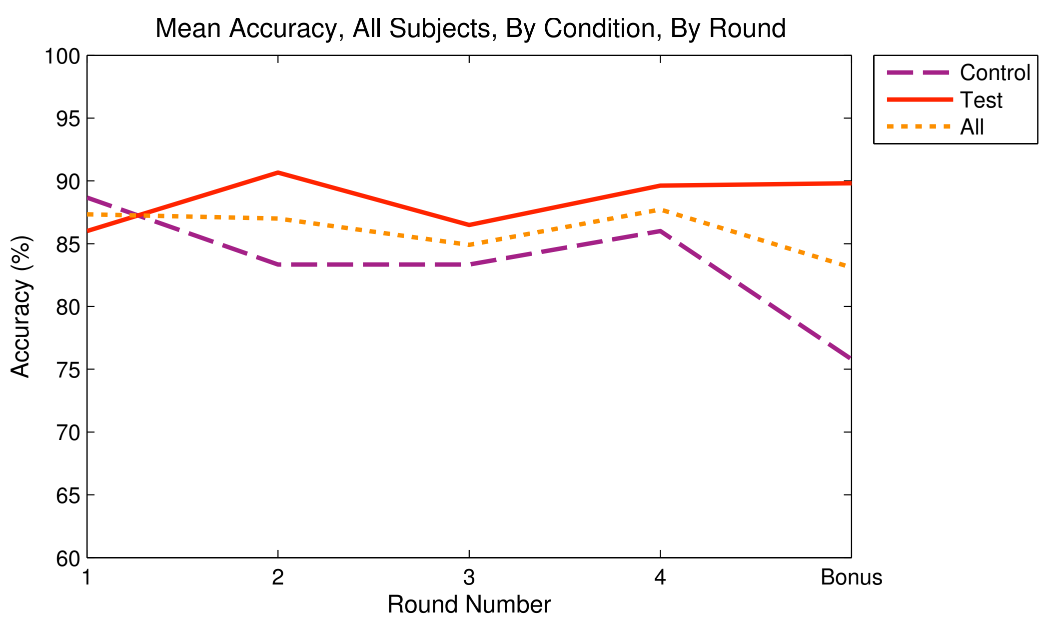


Figure 4.4: The mean accuracy across all subjects for each round, for both conditions.

condition over the course of the experiment. To see if the order of the conditions had an effect we look at mean latency across all subjects for by the order the conditions were completed, test or control first (Figure 4.10). A paired t-test revealed no significant difference between the the mean latencies

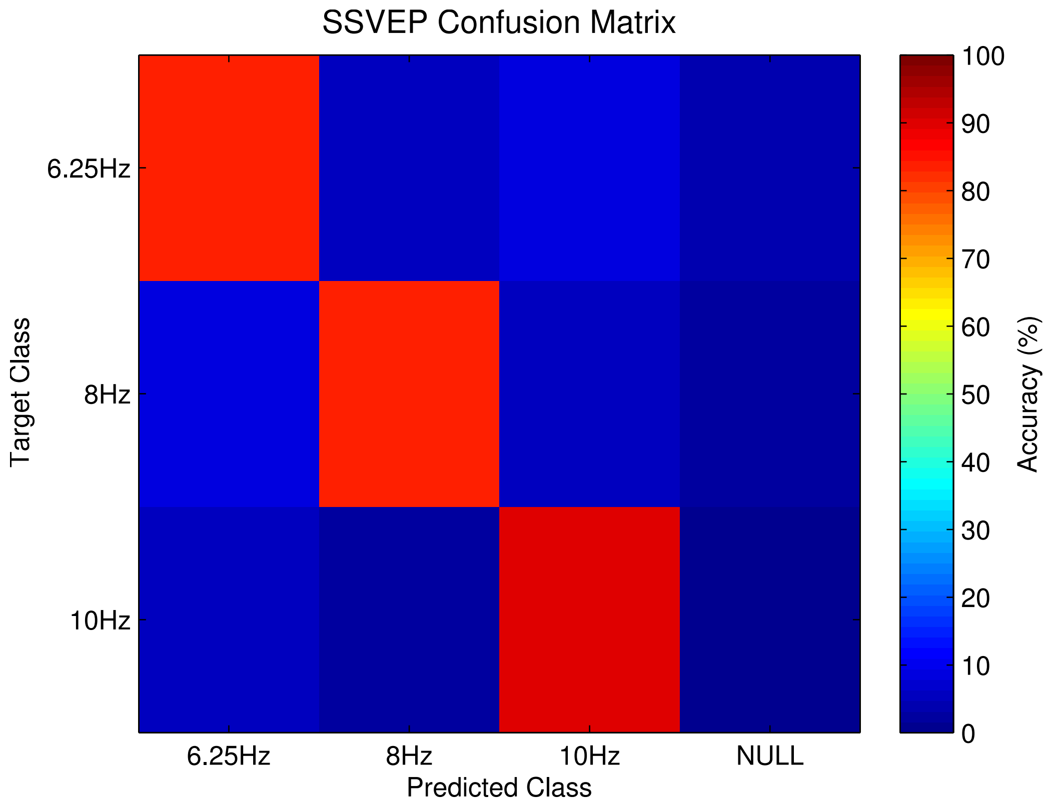


Figure 4.5: This confusion matrix represents the instances of classifications for each frequency. The "NULL" column represents when no class was predicted.

in the condition completed first and second.

4.3 Task Completion Rates

We define task completion rates to be the percentage of trials completed for both conditions. For the task completion rates we consider only the first four rounds. The fifth round was used as a free play round and therefore each participant completed a different number of trials. All subjects, except one, completed all four rounds for both conditions. During one subject's fourth round in the last condition there was a small technical difficulty with the EEG equipment and recording was stopped. We believe if this technical interruption had not occurred the participant would have finished all four rounds. In any case, the task completion rate for the study was 97.5%.

We look at the number of trials completed and time spent in the bonus

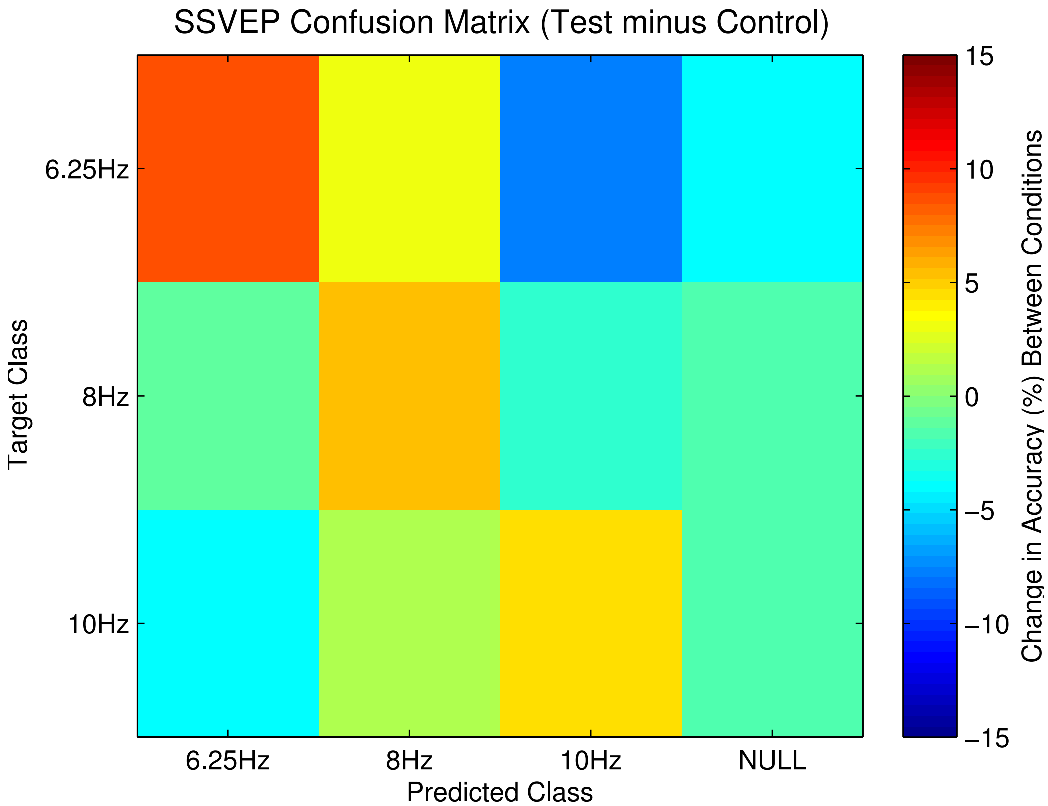


Figure 4.6: This confusion matrix represents the instances of classifications for each frequency. The "NULL" column represents when no class was predicted. The confusion matrix displays the differences between the two conditions by subtracting them(test minus control).

round as a metric of engagement. Participants completed a total of 252 trials in the control condition and 275 trials in the test condition. Figure 4.11 shows the mean number of trials completed per condition. Figure 4.12 show the amount of time spent in the bonus round by condition. While there were more trials completed and more time spent in the test condition, a paired t-test showed this difference was not significant ($t(9)=0.18$, $p=0.85$).

However, a difference was found in the number of trials completed in the bonus round as a function of order. Participants completed significantly more trials in the first round they completed (M: 38.6) than in the second round they completed (M: 14.1) ($t(9)=2.55$, $p=0.03$) (Figure 4.13). Correspondingly the time spent in the bonus round was also effected by order (Figure 4.14). We speculate this result is due to a decreasing interest in the BCI application as the study went on. This result indicates the importance of the amount of time each experiment takes. It is possible children were

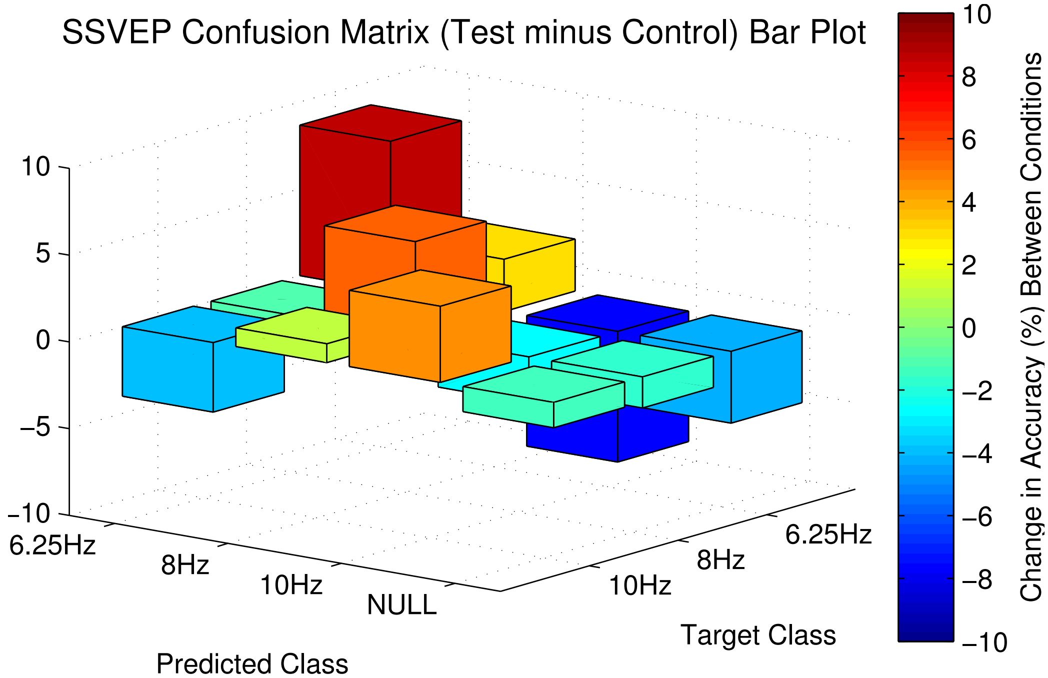


Figure 4.7: This confusion matrix represents the instances of classifications for each frequency. The “NULL” column represents when no class was predicted. The confusion matrix displays a 3D representation of the differences between the two conditions by subtracting them(test minus control).

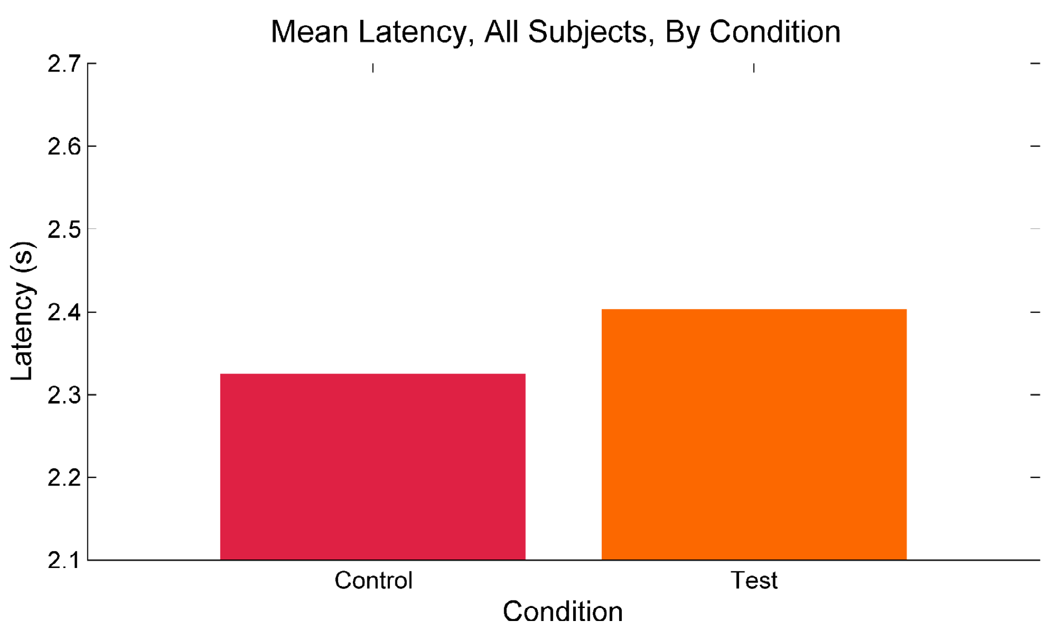


Figure 4.8: The mean latency across all subjects for each condition.

Table 4.5: Mean latency by subject, for each round in the test condition. Blank values indicate that the subject completed no trials for that round. Time is in seconds.

	Round				
Subject	1	2	3	4	5
S01	1.89	1.69	1.75	2.03	1.71
S02	2.09	2.09	2.71	2.70	2.59
S03	2.25	2.59	1.86	2.31	2.76
S04	2.73	2.89	2.75	3.01	2.93
S05	2.14	2.26	2.35	1.99	2.31
S06	2.49	2.34	2.59	2.19	2.33
S07	2.08	2.07	1.97	2.00	
S08	1.55	1.56	1.61		
S09	3.87	3.85	3.86	3.86	3.85
S10	1.64	1.68	1.62	1.66	1.81

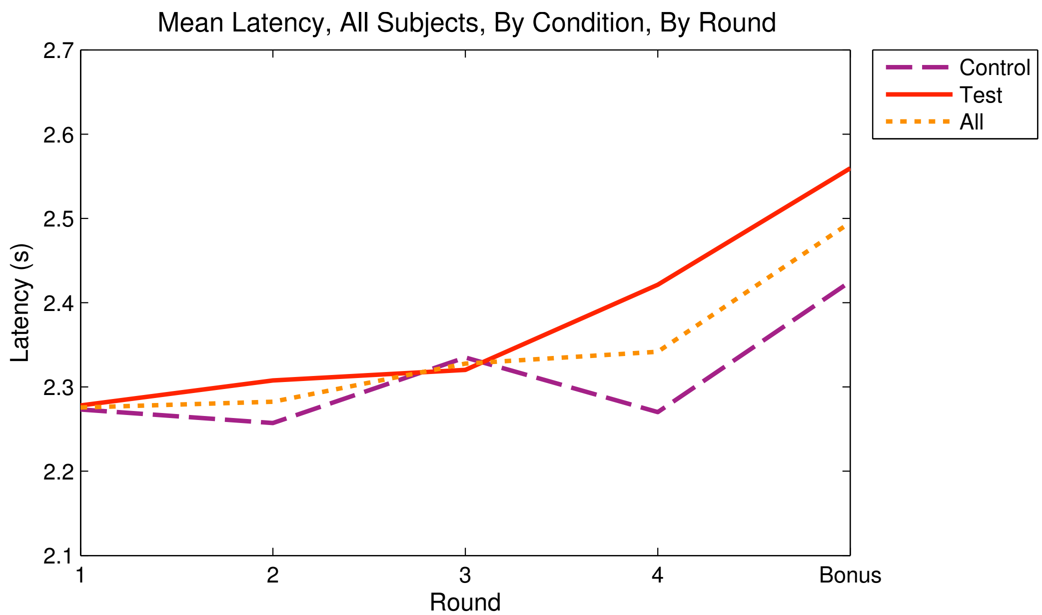


Figure 4.9: The mean latency across all subjects for each condition over each round completed.

getting tired, or ready to move on to something new by the time they were completing the second condition.

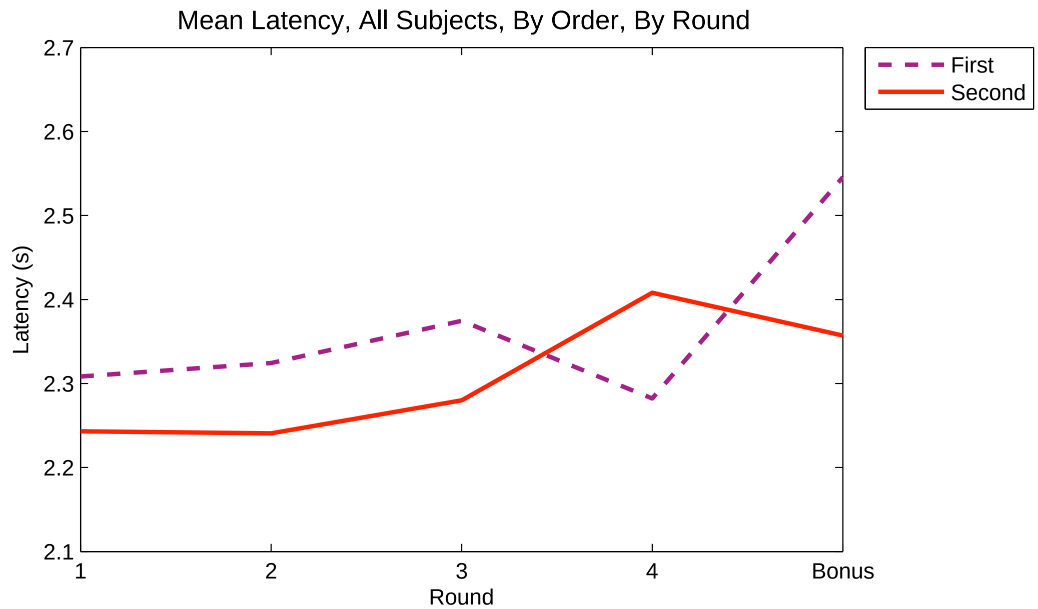


Figure 4.10: The mean latency across all subjects by which condition was completed first and second.

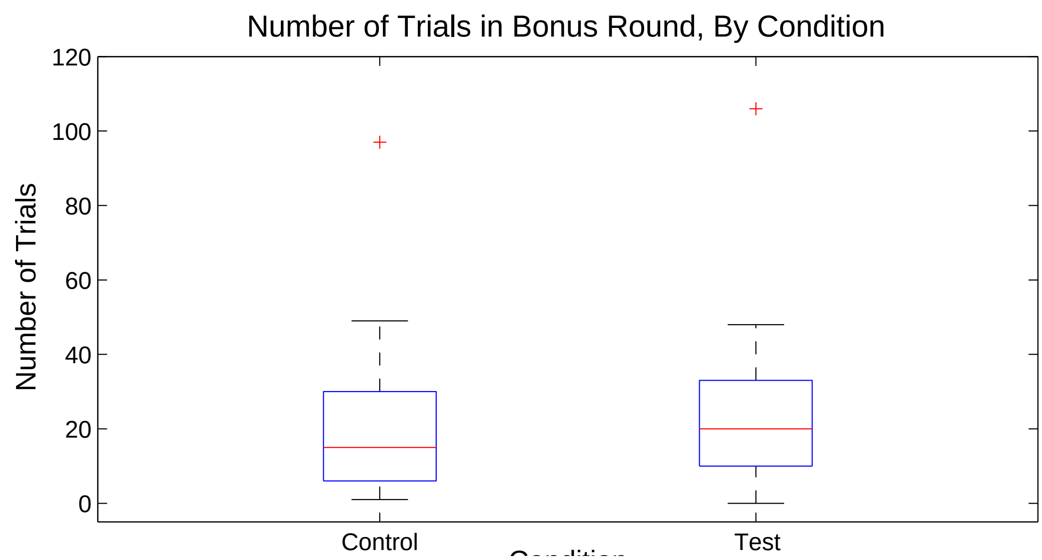


Figure 4.11: A sample screen shot of a the control interface at the end of the session.

4.4 Qualitative Analysis

A total of 10 participants completed the study. Table 4.6 presents the results from the pre-study questionnaire. All subjects answered all of the questions in the pre-study questionnaire. In addition to the results listed in Table 4.6, participants also responded to the question about types of games they

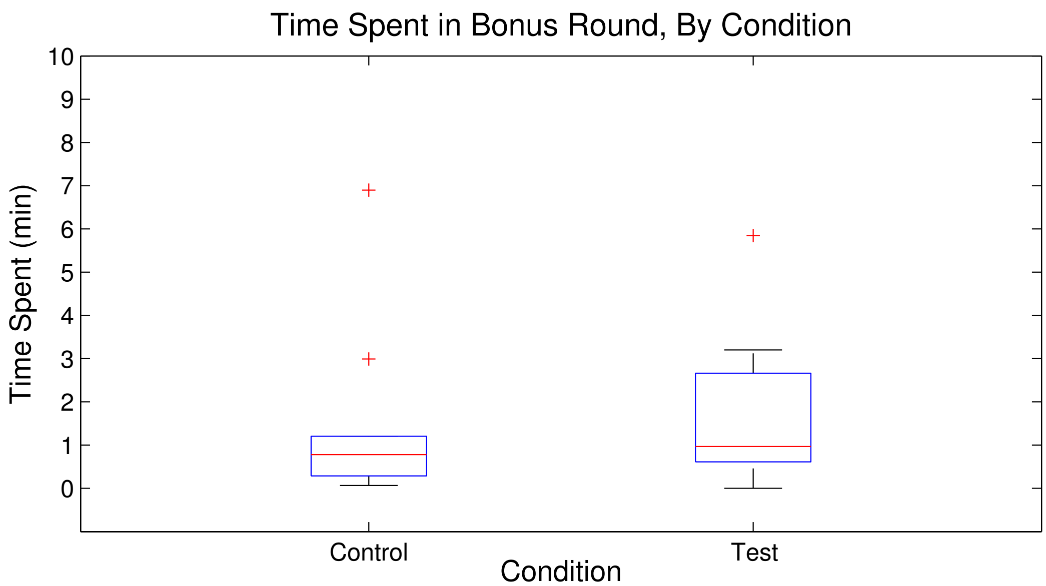


Figure 4.12: A sample screen shot of a the control interface at the end of the session.

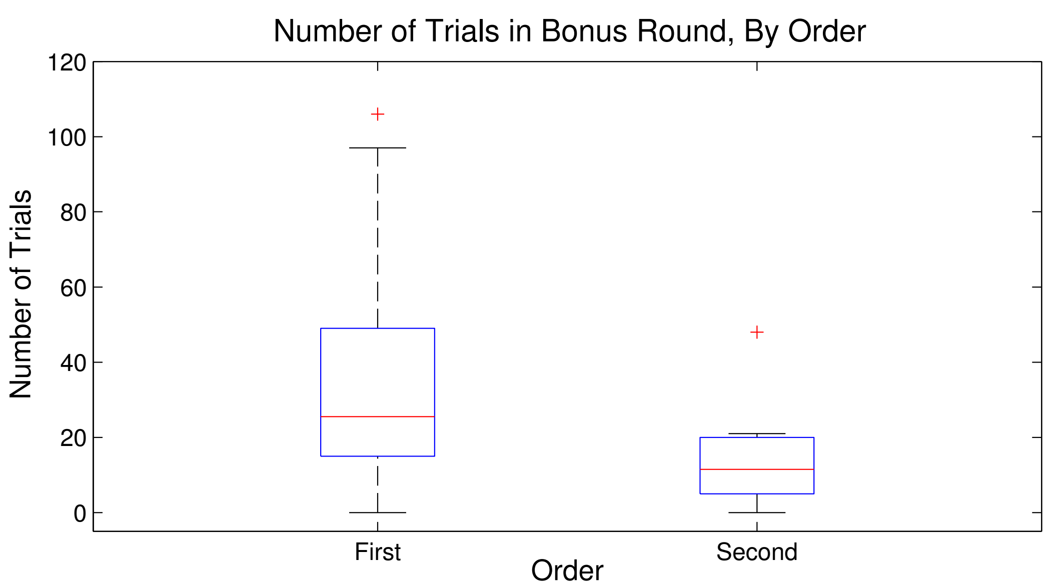


Figure 4.13: A sample screen shot of a the control interface at the end of the session.

liked to play. The majority of the participants liked to play at least one video or computer game. Most participants reported liking Minecraft Some participants also listed sports (such as soccer or basketball).

Before starting the experiment, the participant's level of tiredness was rated on a scale from 1 to 5, meaning "Very Awake" to "Very Tired". A

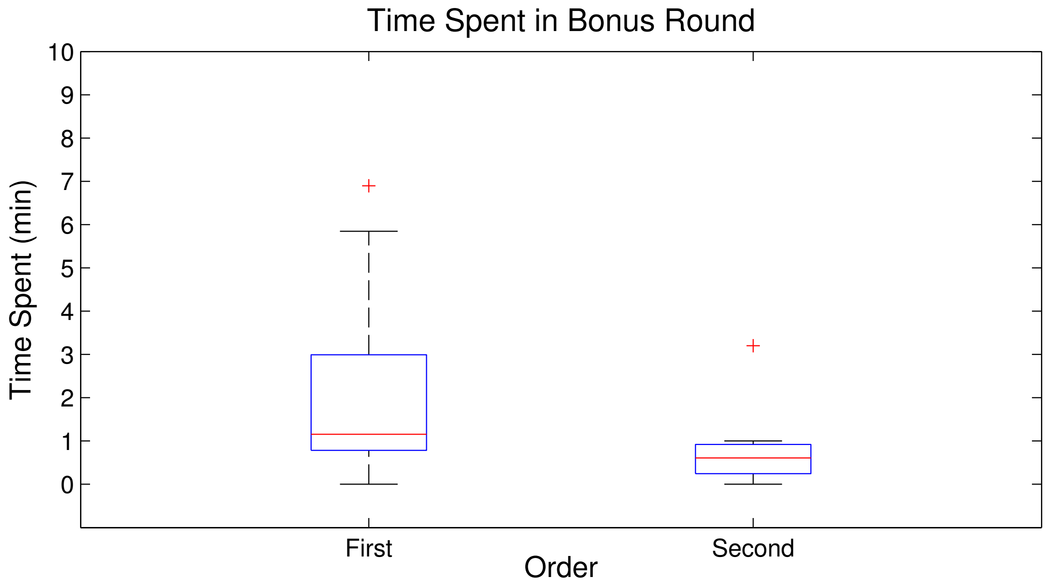


Figure 4.14: A sample screen shot of a the control interface at the end of the session.

scatter plot showing the distribution of mean accuracy with tiredness as a factor is shown in Figure 4.15 and Figure 4.16. Each rating on the tiredness scale received roughly two responses. No clear trend or effect due to tiredness was seen in our results. However, this could be due to a low number of data points per group.

After each condition, participants were asked to complete a post-study questionnaire. Table 4.7 presents the results from the post-study questionnaire. All subjects answered all of the questions in the post-study ques-

Table 4.6: Pre-Study Questionnaire Answers. For the "How tired are you?" question, participants could answer using a 1 (very awake) to 5 (very tired) scale.

Question		Mean Response	SD	Range
Age	9.90	0.74	9-11	
Wears contacts/glasses	Yes = 7 No = 3			
Grade	3rd = 3 4th = 4 5th = 2 6th = 1			3rd - 6th
How tired are you?		2.75	1.18	1-5

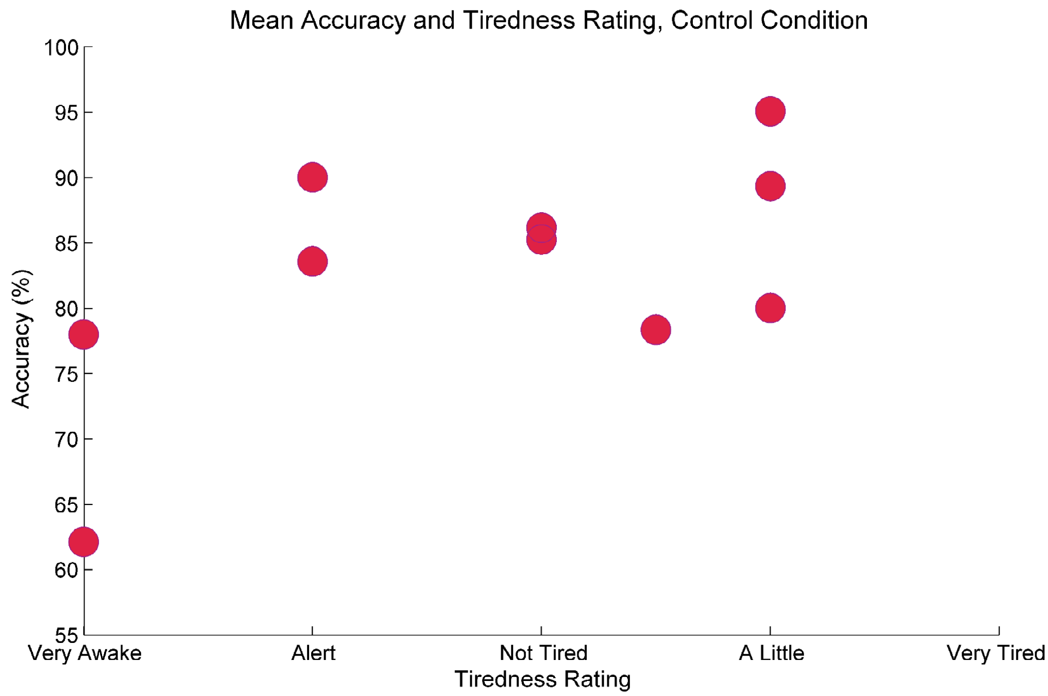


Figure 4.15: A scatter plot of each subject's mean accuracy from the test phase in relation to tiredness ratings.

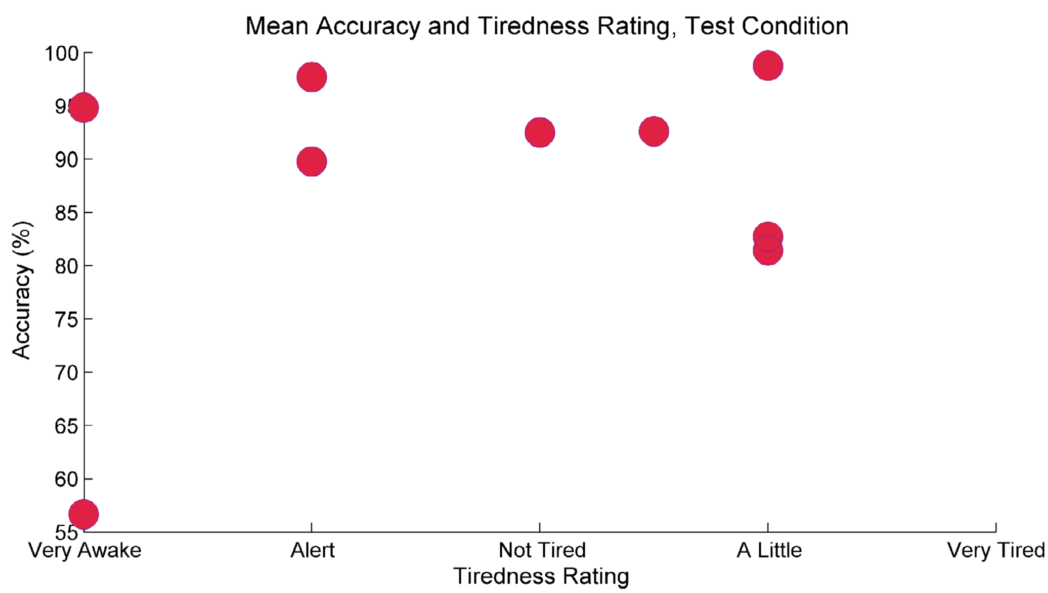


Figure 4.16: A scatter plot of each subject's mean accuracy from the test condition in relation to tiredness ratings.

tionnaire. One participant only completed a survey at the end of the session rather than a survey after each condition and is not included in the table. That subject rated the BCI and application favorably, and marked

Table 4.7: Post-Study Questionnaire Answers. For the “What did you think of the game/application?” and the “What did you think of the BCI system?” question, participants could answer using a 1 (Awful) to 5 (Brilliant) scale.

Question		Mean Response	SD	Range
Control Condition				
Application Rating		4.27	0.83	3 - 5
BCI Rating		4.33	0.86	3 -5
Again-Again	Yes = 4 Maybe = 5 No = 0			
Test Condition				
Game Rating		4.31	0.88	3 - 5
BCI Rating (Test condition)		4.37	0.74	3 -5
Again-Again	Yes = 5 Maybe = 4 No = 0			

“Yes” on the Again-Again table. In general, participants provided positive feedback about their experience with the target selection application, Brain Storm game and BCI system. Upon arrival, most participants were excited to participate in the study and showed interest in the science behind the BCI system. The experimenters observed that participants tended to get a little bored during the BCI system set-up. When this would happen the experimenter tried to make conversation with the participant to keep them engaged. Toward the end of the study children seemed to be ready to take the EEG equipment off and move on to a new activity. Perhaps this indicates that the one hour long study was a bit long for the subjects.

CHAPTER 5

DISCUSSION

Although our methodologies do not strictly parallel those in [31], we believe they are similar enough that we can draw some comparisons. As stated before, [31] found children (mean 9.8 years old) to perform at between 50%-76% accuracy when using an SSVEP-based BCI. Task completion rates for this group of children was less than 60%. These low performance rates were proposed to be due to a difficulty generating signals in the low stimulation frequency range. In contrast to prior research, we observed both higher mean accuracy rates (85.6%) and task completion rates (97.5%) for children (mean 9.9 years old) using an SSVEP-based BCI with similar low stimulation frequencies. This result indicates that children are able to use an SSVEP-based BCI with low stimulation frequencies. The differences in the results may be due to factors such as engagement or distraction.

5.1 Engagement

One difference between our study and the work in [31] is the SSVEP-based BCI application that participants were asked to use. [25] briefly touches on the topic of selecting an attractive BCI application for studies. In that work the researchers selected a robot navigation task rather than a spelling task under the premise that this would attract more participants. In [31] participants used an SSVEP-based BCI application to spell different words. Our experimental methodology asked participants to use an SSVEP-based BCI application for a target selection task and to play a computer game. It is possible participants were more engaged in our applications than in the BCI speller leading to higher overall performance rates. The low task completion rates (mean under 60%) in [31] suggests the participants were not interested in the application, or frustrated with its performance. The participants in our study had high task completion rates (mean 97.5%) and responded very favorably in the post-study survey when asked if they would like to use the BCI again.

Previous studies with children have noted an increase in task completion rates when framing a task in a game in order to engage participants [33]. While the performance differences between the control and test condition were not significantly different, we did notice a higher mean accuracy rate in the test condition. This could potentially be due to engagement or motivation. The use of scoring, prizes, story line and music have previously been identified as useful tools for making engaging games [35]. The elements appearing in "Brain Storm" may have motivated participants to try harder in the test condition. However, the extent to which engagement impacted BCI performance is not clear. We encourage the study of engagement as a factor for BCI performance as a direction for future research. We also encourage researchers to take into consideration the target user group when deciding what applications are selected for studies.

5.1.1 Training

The training phase used in this study asked participants to attend to a sequence of targets by changing their visual attention (for more details see Chapter 3). The training data from this study show participants were not able to reach 100% accuracy given a five second window length with no threshold. The experimenters noticed a trend in which children seemed to develop a strategy for attending to SSVEP-targets while using the BCI during the control and test phase of the study. Children did things such as sit up straighter in their chairs and move their heads to be aligned with the SSVEP-targets. This change in behavior could be in response to getting feedback from the application in regards to which target has been selected. This change in behavior could also indication an increase in engagement during this session. Previous work evaluating engagement has shown that physical movement is linked to levels of engagement [36]. For example, think of when a child plays a video game. When the character on the screen ducks to avoid an object the child may also duck. This small observation acts as a prompt for future studies that explore best practices for training paradigms for children.

5.2 Distraction

Another component we believe may have been a confounding factor is the study environment. In the Ehlers study, children were in a setting that was noted as having a high amount of background noise [31]. Poor performance rates may have been caused by distraction.

On the other hand, the work in [24] and [25] was conducted at a fair, which also may have a high level of background activity and noise. In addition, participants in this study may have been interested in seeing other booths or events. This could have cause distraction. However, the results in [24] and [25] reported high performance rates for the adult participants.

One possible explanation is that children may be more susceptible to getting distracted in an environment with background noise. While noisy environments may give more of a "real world" setting, lab setting may be appropriate for these early studies with children and SSVEP-based BCI applications.

In our work, participants were in a sound attenuated room with little to no background noise. While we tried to limit distractions, our study did not strictly control for background noise and activity. Therefore more in-depth analysis is needed to understand the relationship between environment settings and/or distractions and SSVEP-based BCI performance for children.

5.3 Stimulation Frequencies

[25] found a significant effect on performance as a function of stimulation frequencies. [31] also found a significant effect on performance between different age groups across different stimulation frequencies. Both of these studies demonstrate the importance of SSVEP stimulation frequencies in relation to BCI performance.

The research presented in this study uses a similar set of frequencies as those in [31]. Although our results contradict those in [31], more research is needed to understand how children perform using these frequencies. This study did not directly look at stimulation frequencies as a factor of BCI performance. As an area of future work, this study could be conducted again using multiple sets of SSVEP stimulation frequencies.

The results of our research and the work in [25] and [31] has demonstrated the importance of studying SSVEP stimulation frequencies in relation to BCI population and BCI performance. The differences in the results between these studies motivates future research and contributes to a better overall understanding of BCI demographics.

CHAPTER 6

CONCLUSION

Brain-Computer Interface systems create a direct link between a user's brain and computer. These systems show promise as assistive technology for clinical populations and are also being presented with entertainment applications for a more broad user group. However, the field of BCI still has some obstacles to overcome.

A growing amount of research has been dedicated to understanding reasons behind inter-subject variability in performance. Factors such as SSVEP stimulation frequencies and age have been examined in relation to BCI performance. Studies have shown that a majority of adults are able to effectively use an SSVEP-based BCI. However prior research has suggested an inability for children to use an SSVEP-based BCI with low stimulation frequencies, reporting approximate mean accuracy rates of 50% [31].

Contradicting these results, this study has found that children (mean age 9.9 years old) are able to use an SSVEP-based BCI at a mean performance level of 85.6%. The results of this research suggest that factors, such as engagement and distractions, may have a relationship to SSVEP-based BCI performance. Still, more BCI demographic analysis is necessary to fully understand the extent to which each factor plays a role. For example, while this study was conducted in a quiet lab setting it did not control for or systematically modulate the level of distraction for each subject. We believe it would be beneficial to revisit this in a future study.

The results of this study are important not only because of the potential applications of BCIs for children (such as a rehabilitation tool) but also because they contribute to a better understanding of the SSVEP response in children. Understanding how different components influence BCI performance and the SSVEP response, is important so that researchers can properly set their parameters for optimizing SSVEP-based BCI systems and studies. This work builds on the work of [31] and others, by taking another look at the performance of children using an SSVEP-based BCI. It is our hope that our promising results will motivate more SSVEP-based BCI research with children.

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