CorticoChair: Cognitive Fatigue in Brain Computer Interface Wheelchair Applications

Team 16: Ben Huggard (20798095), Jathushan Kaetheeswaran (20768368), Avery Ryoo (20768594), Srikar Saradhi (20769073), Leon Wang (20765460)

Abstract

A non-invasive brain-computer interface (BCI) is a technology that uses electrodes externally placed on specific areas of the scalp to measure the level of electrical activity, called electroencephalography (EEG), in those regions over time. Recent advances in BCI technology have allowed for medical breakthroughs in accessibility, particularly for individuals who have lost motor function but are cognitively-able. In this report, we outline the initial progress towards the development of a mobility prediction model for a BCI-controlled wheelchair for individuals with quadriplegia that is robust to the dampening effects of cognitive fatigue in neural activity. This wheelchair uses EEG and steady-state visually evoked potential (SSVEP) to classify between four distinct movement intentions and quantify the cognitive fatigue experienced by the user over time. However, research shows that an increase in cognitive fatigue correlates with poorer SSVEP classification when using traditional methods such as canonical correlation-analysis. To combat this, a convolutional neural network was built that uses quantified cognitive fatigue as well as an EEG window to generate a prediction. To demonstrate a proof-of-concept for a BCI wheelchair, the final designed solution integrates this model with an SSVEP interface and an Arduino-controlled car.

Keywords - SSVEP, brain-computer interfaces, quadriplegia

I. INTRODUCTION

Brain-computer interfaces (BCI) are systems that allow communication between the brain and an external machine through the mapping of brain signals. These systems can be either invasive or non-invasive [1]. Invasive BCI systems generally outperform their non-invasive counterparts since the electrodes are implanted directly in the brain, resulting in higher quality electrical signals being read [2]. For non-invasive systems, BCIs measure electrical brain activity with potentials obtained by electrodes placed on the scalp. However, these signals are often contaminated by poor signal strength and noise, making it difficult for good signal classification [2]. The signals extracted are in the form of electroencephalography (EEG) signals and can be acquired without muscle activation. Despite the difficulty of acquiring clean EEG signals, the associated risk of non-invasive BCIs is much lower compared to invasive BCIs as surgery is not required, and thus is its primary advantage [2]. BCI systems are especially helpful for those with physical disabilities that limit motor functionality [3]. People with quadriplegia, for example, are unable to operate a wheelchair through traditional input devices such as a joystick or a mouse, but they still possess the cognitive capacity to interface with BCI-controlled assistive devices [3]. Voice-activated wheelchairs are an alternative solution for people with quadriplegia, however, this technology is severely limited by the high latency observed between the user's voice command and the motorized output. Therefore, for the practical implementation of a BCI-controlled wheelchair, it is imperative that the user can operate the system within a reasonable latency [4].

Steady-state visually evoked potential (SSVEP) is a common technique used in BCI applications to generate predictable neural patterns which can be mapped to machine commands [5]. Users are shown a series of visual stimuli flashing at particular frequencies, and depending on the stimuli that the user is looking at, signals of the same frequency are elicited in the users' EEG readings, with the strongest activity occurring in the occipital region of the brain [6]. Frequencies above 4 Hz and below 20 Hz are used as they elicit the strongest responses with no particular preference for an exact frequency, given that they are not overlapping in harmonics [7]. Ultimately, this process can allow for standard wheelchair commands to be mapped to the stimuli shown to users. Cognitive fatigue arises when users are exposed to SSVEP visual stimuli for too long and can negatively affect BCI classification performance as EEG signal-to-noise ratio (SNR) and EEG feature separability decrease [2]. This creates a need for a method of control that accounts for cognitive fatigue during BCI-controlled wheelchair usage. Some of the techniques used in current literature that aim to reduce user cognitive fatigue include amplitude-modulated visual stimulation for users, which intends to maximize user attention while minimizing eye strain [3]. However, this technique can inherently decrease BCI classification accuracy, as decreasing the magnitude and frequency of the stimuli affects how clear the SSVEP patterns appear in EEG data. Rest is another common method that can help relieve user fatigue, however, it is impractical to force the user to rest randomly during daily usage, and that there is no standard for user rest defined in current literature [8]. Overall, this project aims to address the current state of misclassifications and latency in BCI-controlled wheelchairs by quantifying and compensating for cognitive fatigue to extend SSVEP stimulation across a larger range of user mental states and to lower risk of user injury and frustration [9][10].

II. PROJECT MOTIVATION, SCOPE, AND OBJECTIVES

The primary motivation of the project is to provide a means for accurate motor control with minimal latency for users with quadriplegia for extended periods of time while accounting for user cognitive fatigue [10]. The latency window includes the extraction of EEG signals, the preprocessing of the raw data, and the inference of the developed model, which accounts for both SSVEP data and cognitive fatigue scores to determine motor classification. The scope of the project is constrained to both the collection of EEG data across five subjects and the development of a model that outputs classifications, which will be mapped to a hardware prototype. The hardware component of the project will simply be a demonstration to illustrate the motorized movements of a wheelchair in response to SSVEP stimuli. Minimizing latency introduced by the firmware to operate the motors and the activation of the motors themselves will not be within the scope of the project. Furthermore, the quality of the motor movement, specifically the degree of turns, speed, and acceleration will not be emphasized in this project. The project's scope includes successfully performing SSVEP experiments and extracting EEG data that can be used for both SSVEP mapping as well as cognitive fatigue calculation. Therefore, it is a crucial objective to evaluate the quality of the signal by identifying electrode impedance and other sanity measures. Additionally, the project's objectives include collecting EEG data across subjects to develop and train a deep learning model that can incorporate EEG data and fatigue calculations to determine SSVEP classifications. Furthermore, successfully quantifying cognitive fatigue and its onset along with recording the latency is another important project objective. Thus, the objective is to design a proof-of-concept system with BCI-integrated wheelchair technology for people with quadriplegia that will measure cognitive fatigue and compensate for it by refining BCI parameters to reduce classification errors of standard wheelchair movement commands.

III. ENGINEERING ANALYSIS AND DESIGN METHODS

III.I ENGINEERING SPECIFICATIONS

**See Appendix A for engineering specifications and the Quality Function Deployment (QFD).

<u>*ES1 - Difference in classification accuracy between non-fatigued and fatigued states*</u>

User Requirement: System performance during fatigued states must be similar to non-fatigued states which will preserve the accuracy of system outputs while promoting user autonomy.

Standard/Academic Findings: Researchers from Xi'an Jiaotong University, China published a journal article in 2016 that compared the offline accuracy of high-fatigue vs low-fatigue and found an approximately 14% decrease [11].

Reasoning: This engineering specification is the main function of this proof-of-concept system. Improving the performance of SSVEP-based BCI systems during high-fatigue periods is an ongoing research problem due to the nature of SSVEP paradigms. These paradigms involve the user engaging in extensive visual stimulation with flickering stimuli, and it has been extensively documented in scientific literature that the increase in cognitive fatigue during these periods negatively affects the signal quality and classification accuracy of BCI systems [11][12]. We aim to observe an increase in classification accuracy with our solution after a fatiguing task compared to the accuracy of the baseline system after the same task.

ES2 - System latency should not exceed three seconds

User Requirement: System must be safe, easy to set up and improve the user's autonomy.

Standard/Academic Findings: The Neural Rehabilitation and Engineering (NRE) lab advised our team that state-of-the-art SSVEP-based BCIs in current research have a latency of fewer than 2 seconds and that the majority of system latency time is derived from the length of EEG data required for accurate classification [13].

Reasoning: It is critical that the designed solution does not jeopardize the safety of its users who rely on its accuracy and latency for aiding mobility. This is a critical metric for ensuring that users can safely move autonomously using the designed solution, and our method of compensating for cognitive fatigue should not increase this latency to a degree where it is hazardous for the user. For our system, latency would be defined as the time between when the user focuses their attention on a flashing stimulus and when the system outputs a classification based on this change in input and moves the model wheelchair [14]. This benchmark was determined through a combination of literature reviews and conversations with the NRE lab that indicated 3 seconds was an acceptable latency given the scope of this project.

ES3 - Quantify cognitive fatigue

User Requirement: System must quantity fatigue during real-time EEG acquisition.

Standard/Academic Findings: Using a passive BCI system, researchers in the aerospace industry found that pilots experienced an increase in cognitive fatigue during more challenging flight tests, which led to the pilots missing more auditory cues compared to their non-fatigued states [15].

Reasoning: As stated in ES1, the primary function of this solution is to mitigate the detrimental effects of cognitive fatigue on SSVEP-based BCI systems. To achieve this, the system must quantify the level of cognitive fatigue the user is experiencing through real-time EEG data. Although cognitive fatigue is subjective and varies between users, it is expected that there is an increase in cognitive fatigue after the user completes a fatiguing task [15]. The accurate identification of periods of increased cognitive fatigue is critical to ensuring that the final solution is able to effectively compensate for the lower SNR during these periods.

ES4 - Weight of the system must not exceed 300 grams

User Requirement: The system must be lightweight, safe, and easy to set up.

Standard/Academic Findings: Research examining the effect of virtual reality (VR) device weight on user comfort found that 300 grams was the threshold at which users experienced discomfort from the attachment on their heads [16].

Reasoning: The final product must not include additional hardware that is spacious or heavy as this would impede the daily usage of the wheelchair. The only hardware considerations we need to focus on are the screen which displays the stimuli and the EEG system itself. The former is not a consideration for the project as the project is confined to a lab setting where the research team will provide an external display to the user. The latter can be narrowed down to the weight of the EEG control device and the EEG cap. There is little documentation on the effect of weight on user comfort so reference to academic findings on VR device comfort for our benchmark of

300 grams will be used. Fortunately, the current Mentalab Explore system is approximately 50 grams, so we are satisfying this condition [17].

<u>ES5 - Standard wheelchair commands - rotate left, rotate right, go forward, stop</u>
User Requirement: The system must be safe and promote the autonomy of users
Standard/Academic Findings: The NRE lab advised the team to limit the number of controls for design simplicity, and the team opted to choose 4 basic wheelchair commands that have been used in BCI wheelchair research previously [18].
Reasoning: The final specification is related to the original function of the project - to control an electric wheelchair using an SSVEP-based BCI system. Users of the system need to be able to choose different commands based on their desired movement pattern, so building an SSVEP-based BCI system that offers multiple stimuli/command options is one of the engineering requirements for this project. Although the team does not currently have access to an electric wheelchair for implementing these commands, the team will replicate the wheelchair using a model for testing and validation.

III.II QUALITY OF DATA

The success of the designed solution is dependent on analyzing the EEG data that is acquired during non-fatigued and fatigued states. Therefore, it is imperative that there are calibration checks in place to verify that the data has a high SNR. The first of these checks is an electrode impedance test. The electrode impedance test works by calculating the impedance between the electrodes and the scalp, so a lower impedance is desirable in order to remove noise. Scientific literature suggests that optimal impedance values are between 5-10 kΩ, so data will be considered adequate if it meets this benchmark [19]. Next, the placement of the electrodes must stay consistent across experiments and users. This means that the calibration process should include centering and fitting the EEG electrode cap such that the electrodes are placed in the appropriate locations of each user's frontal, parietal, and occipital lobes. However, even if the setup passes these checks, the streamed data may still contain high levels of noise. To avoid this, the setup will acquire EEG data where the user is blinking and when their eyes are closed. The presence of blinking artifacts in data can be seen as period spikes in signal amplitude, and shows that the system is able to detect quick changes in signal amplitude [20]. Additionally, an increase in alpha band spectral power should appear when the user closes their eyes for a few seconds, and suggests that the EEG headset is identifying useful data rather than noise [20].

III.III FATIGUE SCORE CALCULATION

To address ES3, the cognitive fatigue experienced by the user must be defined in a quantifiable way. Ideally, this would be formulated as a function of EEG signals, for ease of integration with existing BCI paradigms for which EEG is typically the only input. Souza et al. conducted a review of studies of cognitive fatigue and found significant patterns in EEG band powers correlating to levels of fatigue induced by the experimenters [21]. A summary of their results is depicted in figure 1. Eight studies found band power increases in the α and Θ frequency bands and decreases in the β band in the frontal lobe as cognitive fatigue progressed. A "fatigue score" was therefore defined as the ratio $(\alpha + \Theta) / \beta$. It was theorized that this value would capture the reported behaviour and act as a scalar representation of the level of cognitive fatigue in the user.

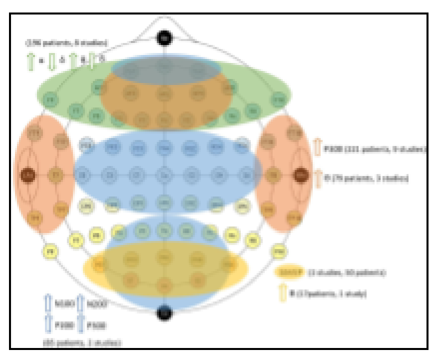


Figure 1. Regions of the brain affected by cognitive fatigue [21]

III.IV BASELINE CCA

CCA was chosen as the base classification model to which the designed solution would be compared. The CCA algorithm involves comparing the EEG window to the sinusoids of the SSVEP frequencies. A correlation is calculated between the EEG signal to each of the frequencies, and the model chooses the highest value as its prediction [22].

III.V EXPERIMENT SETUP (TRIAL, FATIGUE, TRIAL)

The experimental protocol for this project was designed through conversations with the NRE lab. It was determined that an ideal protocol for exhibiting the effect of fatigue on SSVEP-based BCI performance would be to have two experiments of the same length separated by a fatiguing task. The reason for a fatiguing task as opposed to prolonged usage is that it would save time during the data collection period and allow the team to better control how fatigued the user becomes. Since fatigue is a relative measurement, the team narrowed down a set of activities that would elicit cognitive fatigue in a short period of time. Based on literature in the field, the primary tasks were arithmetic tasks, the Stroop test, maze navigation, and the dual *n*-back test [23]. Among these, it was determined that dual *n*-back tests provided the team with more control over the difficulty of the fatiguing task while invoking fatigue with high confidence based on existing research.

The experiments before and after the fatiguing tasks were designed after consulting with the NRE lab over the protocol that would provide enough useful data for informing a possible solution. A training set with 200 2-second EEG samples per group member (200x5=1000 samples in total) was deemed to be the minimum acceptable amount. Over multiple sessions, 400 samples were collected from each member, for a total of 2000 samples. A fatigue score was calculated from and assigned to each of these samples. The data from this experimental setup was expected to be used in informing a final solution.

III.VI MODELING THE WHEELCHAIR

Given the current time constraints and resources, a model wheelchair was prototyped to represent standard movement commands of an electric wheelchair. This model required an Arduino UNO board and a HC-06 Bluetooth module in order to receive BCI system decisions and output wheelchair movements [24]. Bluetooth was chosen as the main mechanism of short-range wireless communication as it is robust and easy to use [25]. Additionally, the Bluetooth modules used in the design were inexpensive and easy to interface with. Bluetooth communication latency was analyzed as overall system latency had to be minimized. Current literature suggests that Bluetooth latency is negligible when compared to the solution's latency time as it ranges on the millisecond scale [26]. For each decision made by the BCI system, the decision would be sent through Bluetooth to the model wheelchair. This would be done through an HC-05 Bluetooth module connected to the experiment laptop. In terms of model output, an Arduino UNO board connected to the model would contain uploaded C++ code that would output the standard movements outlined in the team's last engineering specification. The C++ control code would include commands to move the model's wheels at certain speeds by sending pulse-width modulation (PWM) values to designated motor control pins using Arduino's built-in `analogWrite()` function. For forward movement, the Arduino UNO board would send PWM values of 250 to both motors. For left and right turns, one motor would be controlled to rotate in the respective direction of the turn while the other rotates in the opposite direction. This is to allow for quicker turns by leveraging both wheels to rotate.

IV. SOCIAL, ECONOMIC, AND ENVIRONMENTAL IMPACTS

The greatest social impact of this design is the direct benefit that it would provide to the stakeholders. The primary stakeholders are quadriplegic persons who are viable candidates to use a BCI-controlled wheelchair. Successful mitigation of the effect of cognitive fatigue in BCI-controlled devices would improve their usability. By allowing users to use their devices for longer periods of time, they would experience greater independence and a capability to go about their daily activities for longer periods without interruption. Better overall performance of a BCI-wheelchair system should result in more frequent use of the system and promote increased adoption of the technology. These effects would improve the overall quality of life of the population of quadriplegics eligible for this type of system.

There are some indirect economic impacts on the stakeholders of this device. Primarily, an improved BCI system that sees greater adoption by the quadriplegic community would lessen some of the financial burden resulting from the care of these individuals, since fewer caretakers may be required to assist the users if they are more capable of completing their daily activities independently.

The environmental impacts of this device are relatively minor. The main environmental concern involved with the widespread adoption of this system would be a lack of sustainability due to the materials used for construction. The design does not involve any major components that would need to be regularly replaced and would be powered by electrical motors running off of a rechargeable battery. As a result, the per-unit environmental impact would be quite low. With quadriplegia's prevalence of around 3 per 100000, the overall impact of this system on the environment would be relatively low and of minimal concern [27].

V. DESIGNED SOLUTION

V.I GRAPHICAL USER INTERFACE (GUI)

In order to design SSVEP experiments, the team developed a Python GUI (see figure B1 in Appendix B) that interfaces with the BCI system. This application allows the user to access functionality such as impedance values and sanity check information, and the ability to customize SSVEP experiment parameters such as duration, frequencies, and classification methods. The use of this application was important for ensuring that experiments were reproducible and that there was control over how data was collected, analyzed, and stored.

V.II SANITY CHECKING

In order to verify that the EEG data being streamed to the system was good, the team implemented a sanity checking feature for the Python application. These checks involved the recording and analysis of two short experiments: periodic blinking and eyes-closed. After the EEG data is recorded, the data for each electrode is passed through a bandpass filter from 1 to 40 Hz to remove electrical and low-frequency noise. After plotting the time series data for each channel, the application computes the power spectral density (PSD) using Welch's method and outputs a spectrogram. After visually inspecting these test results, the team would proceed with the rest of the experiment as there was a high level of confidence that the system is acquiring useful data as opposed to noise [20].

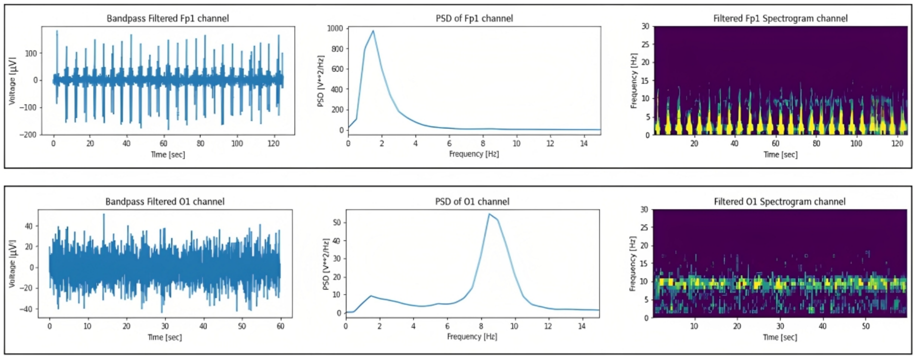


Figure 2. Raw EEG data, PSD, and spectrogram of sample user's blinking data (top) and eyes-closed data (bottom).

V.III RECORDING FATIGUE

Fatigue score calculation was performed in real-time during experimentation. The ratio $(\alpha + \Theta) / \beta$ was calculated from PSDs of the EEG data. The PSDs were obtained through Welch's method, using a segment length of 2 seconds. Since overall cognitive fatigue changes were expected to take place over long timescales, on the order of minutes, the fatigue score was calculated over a relatively long window to smooth out higher frequency noise in the signal. This calculation was performed every 2 seconds on 4-minute windows of EEG data recorded from the Fp1 and Fp2 electrodes placed on the frontal lobe. The result was a scalar fatigue score value available every 2 seconds for consumption by the classification model.

V.IV CNN WITH FATIGUE ARCHITECTURE

The classification model was inspired by the one designed by Aravind Ravi, a Ph.D. candidate in NRE Lab and a secondary supervisor of the capstone team, for the classification of SSVEP signals [22]. The preprocessing procedure remains the same, but the architecture of the model itself has been significantly reworked to account for the difference in the number of classes as well as a desire for better performance.

The preprocessing involved accepting 2-second windows of EEG data from the 8 channels of the BCI. At a sampling rate of 250 Hz, each input had a shape of 8x500 (# of channels x # of seconds*sampling rate). Each channel was processed by a 4^{th}-order bandpass filter between 4 Hz and 40 Hz, and then with a fast Fourier transform. The real and imaginary values of each channel were then concatenated as a single vector, resulting in a processed input of shape 8x72 (# of channels x combined # of real and imaginary powers). This data is referred to as the complex powers input. Additionally, the fatigue score was calculated on each window of EEG data. This singular scalar value is referred to as the fatigue input.

A CNN was chosen as the model for this SSVEP classification task. The complex powers input is processed sequentially by two Conv2D-BatchNorm-ReLU (CBR) blocks and then by two densely-connected linear layers. The CBR blocks have three stages. First, the data is processed with a number of convolutions, of which the weights are learned during the training process. While it is impossible to fully understand the purpose of each trained convolution kernel, they are thought to identify low-level features in the data earlier on in the model. Next, the convolution-filtered data is standardized. This step allows for an expedited training duration. Finally, the ReLU (Rectified Linear Units) activation converts every negative element value to 0. This allows the model to capture non-linear relationships in the data. Additionally, each CBR

block is followed by a dropout layer that randomly deactivates a specified percentage of neurons. The exact parameters of the CBR blocks are specified in Table C1 of Appendix C.
The output of the second CBR block is flattened to a one-dimensional vector and is then sent to two densely-connected layers. Each neuron of the densely-connected layers is a weighted sum of all of the neurons of the previous layer. The fatigue input is concatenated to each of the densely-connected layers. The final densely-connected layer has four elements, and the softmax function is used to force the sum of these element outputs to equal 1. The class corresponding to the element with the largest value is then chosen as the classification.

V.V SYSTEM SETUP AND MODEL WHEELCHAIR DESIGN

The Mentalab BCI as well as the EEG cap and electrodes were provided by WATOLINK as “off-the-shelf” products that were necessary for completing this project. The system starts with the Mentalab BCI reading and outputting a classification based on a user’s EEG readings when they were looking at an SSVEP stimulus. This classification is first received by the laptop running the SSVEP experiment and is then sent to a connected Arduino UNO with an HC-05 Bluetooth module. This module receives the BCI decision as an index based on the positioning of the stimulus frequencies shown to the user and then sends it to a paired HC-06 module. Each of the indices is mapped to a wheelchair command and is processed by the Arduino UNO connected to the model wheelchair. The model consists of 2 motors with attachable wheels, a battery pack, an HC-06 module with an Arduino UNO, and an L239D driver. The chassis of the model was purchased as a package which contained a plastic frame, 2 motors with attachable wheels, and a battery holder that could house four 1.5 V batteries. To properly control the model’s motors, an L239D driver connected to a breadboard had to be attached to the chassis and wired to each of the motors. This driver contains an internal H-bridge which controls the rotational direction of the motors and wheels and was an “off-the-shelf” product that was added separately to the chassis. The Bluetooth module and Arduino board were also connected to the breadboard attached to the model and were powered by four batteries. This setup allowed for the model to wirelessly receive decisions from the BCI system. Figure F1 in Appendix F shows a system diagram of the system setup.

VI. DESIGN EVALUATION AND VALIDATION

Throughout the course of the project, the team applied an iterative design approach to adding new features to the system. To evaluate and validate the overall design solution, testing protocols that focused on the solution's subsystems were iteratively created based on discussions within the team and with the NRE lab. This allowed for quicker and more efficient testing and validation and for the team to identify key components of the system that could be improved. These protocols targeted the system’s major subcomponents: fatigue quantification, the CNN classification, and the model wheelchair. The performance of the system’s CNN, specifically its classification accuracy, was the main benchmark used in evaluating the CNN. System latency, which is the time taken for the system to output a classification and move the model wheelchair, was used to evaluate if the final solution was able to meet the team’s specification of 3 second latency or less. Ideally, the system should have its accuracy maximized while its latency is minimized. Furthermore, the model wheelchair was evaluated based on whether the four standard wheelchair movements could be completed. By evaluating the performance of each subsystem, the team can determine if the final solution meets the team's engineering specifications and can validate the overall design solution.

VI.I MEASURING COGNITIVE FATIGUE

Cognitive fatigue quantification was evaluated by comparing the fatigue score value between experiments run before and after the dual *n*-back test was performed. This comparison was done by calculating the mean and median fatigue scores in each experiment, and a manual check was performed to observe any patterns that occurred. The ideal result would be a consistent increase in average fatigue score when comparing pre and post-fatigue experiments. The results are displayed in Figure D1 of Appendix D. Out of 10 trials of data, seven showed an increase in fatigue score after the fatiguing task, and three showed a decrease. These results show a very weak correlation between fatigue score and actual cognitive fatigue.

VI.II CLASSIFICATION PERFORMANCE

The performance of the solution was evaluated against the baseline CCA model by using the same testing framework. Classification accuracy for 100 predictions before and after the dual *n*-back test was recorded for both the baseline CCA and CNN model. As shown in figure 3, accuracies for CCA of the three users after the fatiguing task had either stayed the same or decreased as expected. However, user A had a slightly higher classification accuracy post-fatigue when using CNN for classification. Additionally, users A and B had higher post-fatigue accuracies when the CNN was used. This shows that there was an improvement in accuracy compared to the baseline CCA model and satisfies our first engineering specification ES1 (see Section III.I). However, the validation dataset used was small, and although these results are promising, it is important to evaluate the performance of both models across a larger group of users. Due to time constraints, the team was unable to collect this larger dataset for validation, however, the current results on this small population indicate that the final prototype satisfies ES1.

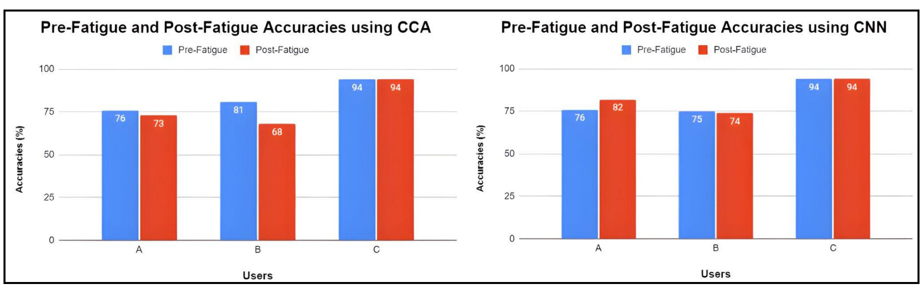


Figure 3. Pre and post-fatigue classification accuracies using CCA and CNN

VI.III SYSTEM LATENCY

System latency was evaluated by recording the time taken for the system to make a classification, send the decision to the hardware, and for the model wheelchair to output a standard wheelchair command. This was done by recording the latency for 20 decisions and averaging the times. For Figure E1 of Appendix E, the average for the trials was 2.35 seconds. This meets our engineering specification outlined in ES2 which is to have a system latency under 3 seconds.

VI.IV WHEELCHAIR COMMANDS

Table 1. Summary of testing protocol for the model wheelchair

Specification	Testing Category	Assessment Criteria
R1	Rotations	Are the left and right turns balanced?
C1	Control	Are the wheels to each turn activating as expected?
C2	Control	Can the model perform a left turn, right turn, forward motion, and stop?

The model wheelchair's rotation was evaluated through specifications C1 and C2. The simplified model was programmed to turn at a 90^{o} angle for both left and right turns. To evaluate specification R1, 20 left and right in-place turns were completed to assess if the model was able to rotate at a 90^{o} angle in both directions and return to its original position. After two consecutive opposite turns, the model's position was visually inspected and any positional differences from its starting position would be noted. Throughout the course of the testing period, it was observed that the machine would undershoot at most 12% of its turns, translating to a 80^{o} turn. The team did not view this slight undershoot as a critical issue as the project's primary objective was the accuracy of the system's decisions rather than the performance of the wheelchair.
For specification C1, the physical behaviour of the wheels was evaluated visually by sending each command to the hardware and verifying that the wheels turned accordingly. Specifically, the forward command moved both wheels, the stop command did not move any wheels, and the left and right turns moved one wheel forward and the other backward. In order to test C2 and verify that the model was able to perform the 4 basic commands outlined in ES5 (see Section III.I), a 2 by 2 meter open space was created for navigation. The user was prompted to engage in an SSVEP experiment for 2 minutes. The behaviour of the model was visually inspected as the user was guided to look at each stimulus corresponding to a wheelchair command. It was confirmed that the model wheelchair was able to perform all 4 commands successfully.

VI.V VALIDATION

The team was able to validate the designed solution by determining whether each engineering specification was met, and concluded that the design solution had met all of the proposed specifications, with the exception of ES3. In terms of classification accuracy, the CNN had higher accuracies for users A and B in a fatigued state when compared to a non-fatigued state. User C was able to achieve the same accuracy level in both a non-fatigued and a fatigued state. This is in contrast to the baseline CCA model which showed an overall decrease in classification accuracy for fatigued users. These results satisfy our first engineering specification. In terms of system latency, the designed solution was able to output a standard wheelchair command in 2.35 seconds, which is better than the team's latency specification of 3 seconds. The system was also able to calculate and quantify a fatigue score, however, the usefulness of this calculated score is unclear. Testing was done on a small sample of data, and there was only a weak trend observed in the data with 30% of trials showing behaviour opposite to what was expected. Therefore, it cannot be said that this specification was successfully met without more testing taking place. Finally, in terms of system weight, the team used Mentalab's BCI kit which contains an EEG cap, a processing module, and wet electrodes, all of which weigh less than 300 grams and would not provide any discomfort to the user. The design solution was also evaluated to output all of the specified standard wheelchair commands, which meets our last engineering specification.

VII. DESIGN SAFETY AND REGULATIONS

The team has considered different regulations and incorporated critical safety features in the final design solution. In current literature, the visual stimuli shown to users during trials ranged from 3 to 20 Hz. However, some user groups, such as seizure-prone users, are sensitive to frequencies above 15 Hz [28]. The team chose to use stimulus frequencies ranging from 7.5 to 12 Hz to minimize any visual risks to users and to exempt all users who were prone to epileptic seizures from participating in SSVEP trials. Users will get at least 5 minutes of eyes-closed rest between trials to minimize user discomfort and allow for cognitive fatigue to be accurately investigated [29]. With the use of EEG electrodes and electrode gel, the design solution is classified as a class II medical device as user brain activity is measured and recorded [30]. For the placement of the electrodes, the team followed the International 10-20 system as it is the standard for electrode placement and allows for reproducible and comparable EEG data to be collected [31]. This was achieved by using Mentalab's EEG cap that had markings for specific electrode placements on the occipital, parietal, and frontal lobes [17]. The design also uses wet flat electrodes which require the application of electrode gel to reduce impedance caused by hair and improve conductance with the scalp. Thus, the team is required to consult users about any skin allergies they may have and to use hypoallergenic electrode gel [32]. Furthermore, since the final design includes the control of a model wheelchair, a decision tree was used as a risk assessment tool to allow the team to minimize model collisions with surrounding objects while maximizing user control of the model. This tree, shown in Appendix G, was used to help designated team members monitor and disconnect the model wheelchair in the cases where an incorrect wheelchair command would cause the model to collide with a surrounding object, but also allow for them to choose to intervene depending on whether the decision would not stop the trial entirely. This allows for the team to efficiently and safely stop a trial prior to potential collisions but also allows for trials to continue in cases where misclassifications would not stop the model wheelchair from progressing. For the design's fail-safe mechanism, designated team members would monitor and be responsible for disconnecting the model and exiting the SSVEP experiment in cases where model collisions occur. A team member would be assigned during all experiments as the team's targeted user groups cannot end the experiments themselves.

VIII. LIMITATIONS OF DESIGNED SOLUTION

As a proof-of-concept project, there are a number of limitations that must be reasonably addressed before this solution can be used by consumers. The first limitation is the difficulty and inconvenience introduced by the current setup that is used to collect the EEG data of the user. At the moment, the designed solution uses wet electrodes that are attached to a tightly-fit EEG cap. This requires an individual to insert the electrodes such that they are securely attached to the cap, minimize the amount of hair covering the areas of the scalp where the electrodes are to make contact, and apply a sufficient amount of conductive gel to these regions. This process can be completed by a single non-user individual in under ten minutes but would require a considerable amount of practice before it falls under this timeframe. Any mistake or oversight in this setup process could lead to some or all of the electrodes failing to record meaningful data. As a

consequence, this can lead to poor accuracy from the SSVEP classification model. Therefore, the ease at which the data quality can be compromised as well as the assumed inconvenience of wearing a tight cap coated with gel are some limitations of the current design.
Another limitation is the lack of precise control over the movement of the wheelchair. Currently, the speed of going forward and turning left and right are set at constant values that are unable to be controlled by the user. While this is due to the wheels requiring a minimum speed to successfully turn the wheelchair, it prevents the user from accelerating or decelerating as they wish. Therefore, this is a pretty significant limitation, as having reduced control over the movement-based parameters could pose safety-related issues (e.g., slowing down or speeding up to avoid unexpected obstacles). Additionally, there is no integrated“fail-safe” method for shutting down the operation of the car in the case of a dangerous malfunction and requires an non-user individual to be present during trials.

IX. CONCLUSIONS AND RECOMMENDATIONS

CONCLUSIONS

Over the course of our fourth year, the group completed a prototype of the final system with all vital components for addressing the problem space. A model stand-in for a motorized wheelchair was created and used as a testing ground for validation of ideas. A desktop application was developed to support the configuration of data collection sessions and initialisation of online tests. Finally, an analysis module was created to calculate a fatigue metric from the input EEG data and infer commands from the signal. Validation was performed on this platform to ensure the model met the specifications developed in BME461. Overall, the majority of results were positive, with the prototype meeting 4/5 of the target specifications. The one unmet specification was ES3, for which validation was inconclusive and would benefit from further with a wider range of subjects. There are several recommendations for meeting this final specification, and for improving the design in general.

RECOMMENDATIONS

The quality of a CNN heavily depends on the dataset it is trained on and its ability to generalize to new unseen data. Therefore, it is recommended to conduct more SSVEP experiments across a greater number of users, particularly users of different ages and genders to train a more robust model. Collecting EEG data from people with quadriplegia is another recommendation as it will be more representative of the project’s primary stakeholders. Since cognitive fatigue is a major parameter in the system paradigm, further recommendations include reiterating upon experimental design for inducing and observing cognitive fatigue in users so that an increase in cognitive fatigue can be better observed. Since the SSVEP stimulus frequency is high enough, it is worth exploring time windows smaller than two seconds to reduce overall latency without compromising system accuracy. Furthermore, it is recommended to continue exploring preprocessing algorithms for cleaning and filtering the data prior to the application of the deep learning model to gauge whether there is an impact on performance. Finally, to develop a full proof-of-concept system, it is recommended to integrate a fully functional motorized wheelchair and perform user testing to evaluate the usability of the BCI system.

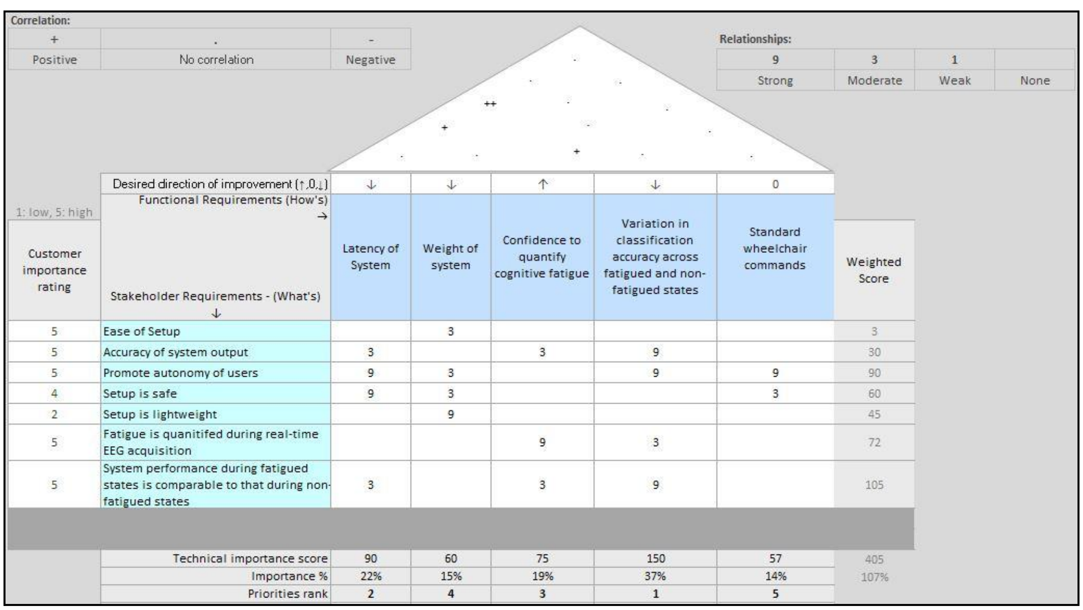
ACKNOWLEDGMENTS

We would like to acknowledge the NRE Lab and the counsel provided by Professor James Tung and Aravind Ravi throughout the duration of this endeavour. We would like to thank Professor Maud Gorbet, Dr. Eric Kubica, and Dr. Calvin Young for their feedback on our project. Finally, we would like to thank WATOLINK for supplying the Mentalab Explore device and providing guidance with operating the equipment.

APPENDIX A

Table A1. Engineering specifications for the designed solution

Engineering Specification	Importance	Description	Required Values	Technical Importance Score (QFD)
ES1	1	Difference in classification accuracy between non-fatigued and fatigued states	Observe an increase in classification accuracy after a fatiguing task compared to the accuracy of the baseline system after the same task	150
ES2	2	System latency	≤ 3 seconds	90
ES3	3	Quantify cognitive fatigue	Observe an increase in average fatigue score for trials after fatiguing task	75
ES4	4	System weight	≤ 300 grams	60
ES5	5	Standard wheelchair commands	Rotate Left, Rotate Right, Go Forward, Stop	57



	Desired direction of improvement (↑,0,↓)	↓	↓	↑	↓	0	
Customer importance rating	Functional Requirements (How's) → Stakeholder Requirements - (What's) ↓	Latency of System	Weight of system	Confidence to quantify cognitive fatigue	Variation in classification accuracy across fatigued and non-fatigued states	Standard wheelchair commands	Weighted Score
5	Ease of Setup		3				3
5	Accuracy of system output	3		3	9		30
5	Promote autonomy of users	9	3		9	9	90
4	Setup is safe	9	3			3	60
2	Setup is lightweight		9				45
5	Fatigue is quanitifed during real-time EEG acquisition			9	3		72
5	System performance during fatigued states is comparable to that during non-fatigued states	3		3	9		105
	Technical importance score	90	60	75	150	57	405
	Importance %	22%	15%	19%	37%	14%	107%
	Priorities rank	2	4	3	1	5	

Figure A1. QFD for the capstone design solution

QFD JUSTIFICATION

The stakeholders in this problem space are the potential users of this technology in the event that it receives clearance to be used outside of a clinical environment. Specifically, people with quadriplegia who would prefer to use non-invasive BCI technology are potential stakeholders for the work presented in this project. One of the primary advantages of using BCI technology is that it promotes autonomy for people with quadriplegia as it allows them to interact with their environment without the direct assistance of a caregiver. As a result, many of the stakeholder requirements in the QFD were developed with this idea in mind. The weights were assigned based on how relevant each of the stakeholder requirements was to the functional requirements.
The primary object of the project is to mitigate the effects of cognitive fatigue on SSVEP-based BCI usage, and as a result, it has the highest importance score associated with it. This is because the improvement of the SSVEP-based BCI system is strongly related to stakeholder requirements of a system that is accurate, promotes autonomy through prolonged usage, and mitigates the fatigue that is currently associated with the technology. Similarly, the latency of the system is one of the primary concerns for stakeholders when using BCIs. Conversations with the NRE lab provided our team with insight that indicated how autonomy and safety are strongly linked to the latency of the system. This is why achieving an appropriate latency is the second most important functional requirement for the team to address.
In order to improve the accuracy of the system during high-fatigue periods, the system must be able to quantify cognitive fatigue in its users. For stakeholders, this information would be valuable to inform themselves of when to take breaks or simply just to improve the accuracy of the system. The functional requirements with the lowest importance are the weight of the system and the commands that are outputted. The weight of the system is important for stakeholders in order to ensure safety and comfort, however, BCI systems are often lightweight and compact so this was not a major factor to consider. Finally, the commands that were outputted could be modified easily by changing the number of SSVEP stimuli, and since the goal of the project was to improve the accuracy of the system the team agreed that this functionality could be a feature to expand upon later.

APPENDIX B

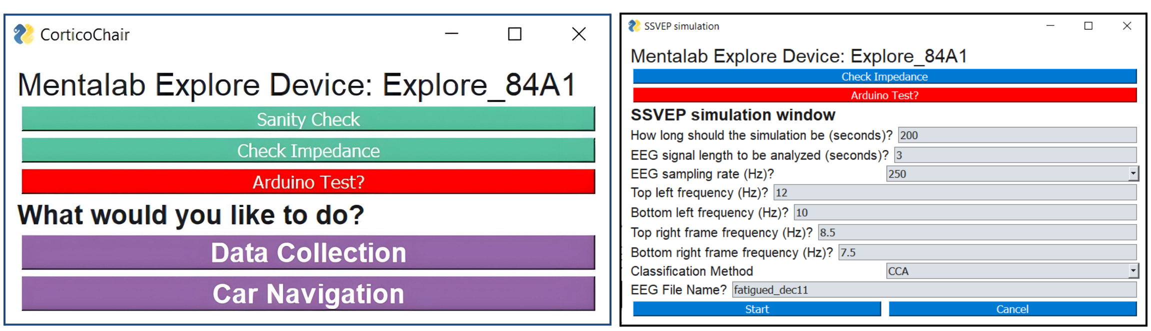


Figure B1. The Python GUI homepage (left) and the input window for designing SSVEP experiments (right)

APPENDIX C

Table C1. Parameters of CBR blocks in the model

	CBR Block #1	CBR Block #2
# of filters	32	16
Kernel Size	8 x 1	1 x 16
Kernel Regularizer	L2 Regularization	L2 Regularization
Dropout	25%	10%

APPENDIX D

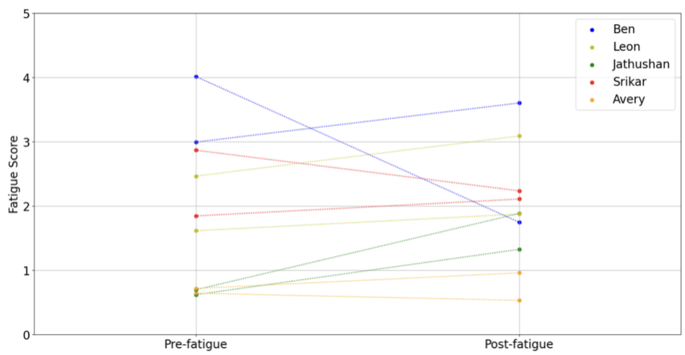


Figure D1. Mean fatigue scores measured before and after a fatiguing task in 10 experiments.

APPENDIX E

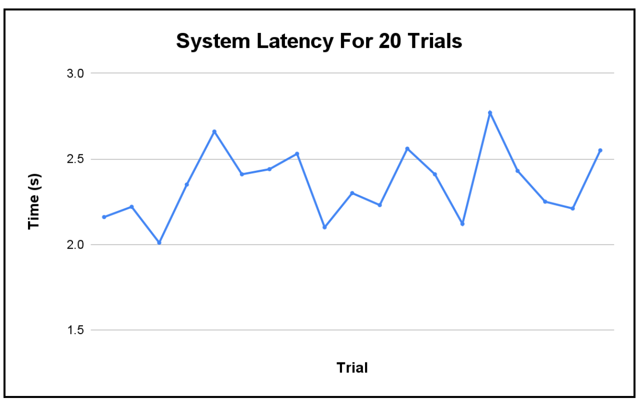


Figure E1. Recorded system latency times for 20 trials

APPENDIX F

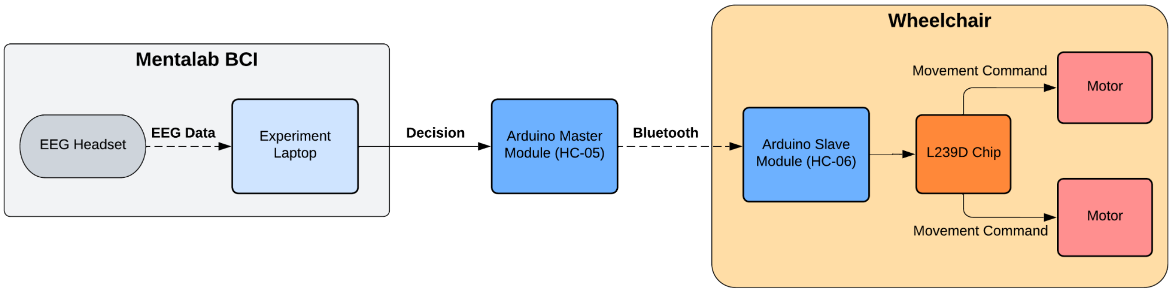


Figure F1. System diagram of the experiment setup and model wheelchair

APPENDIX G

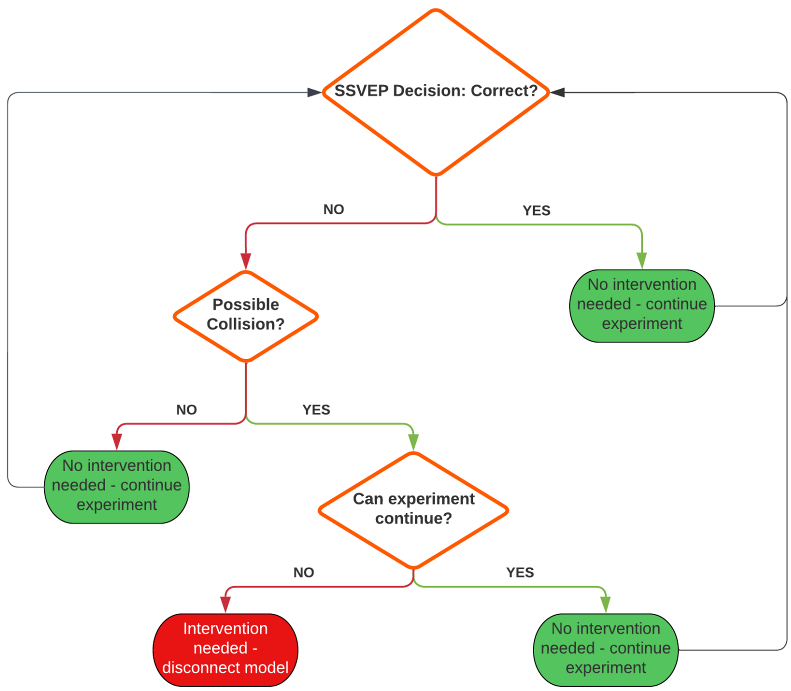


Figure G1. Decision tree for team member to use when monitoring trial with model wheelchair

APPENDIX H

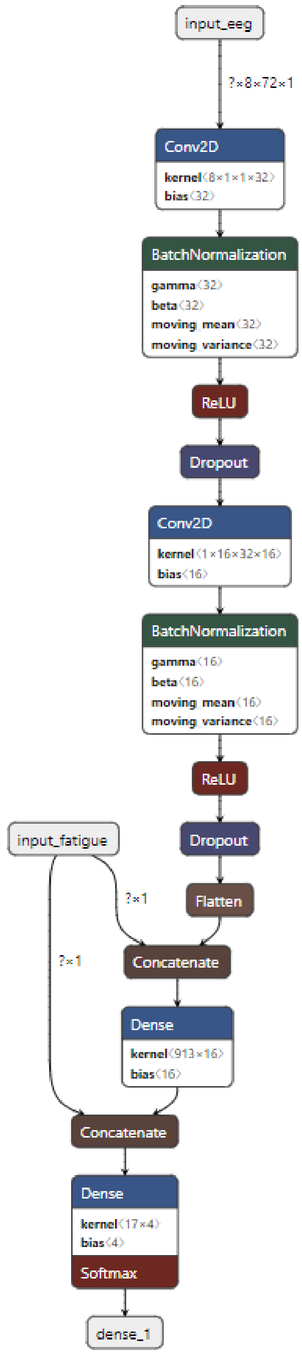


Figure H1. Architecture for CNN model

REFERENCES

[1] L F. F. Nicolas-Alonso, J. Gomez-Gil, “Brain Computer Interfaces, a Review,” *Sensors,* vol 12. no. 2, 2012.

[2] N. Birbaumer, “Breaking the silence: Brain–computer interfaces (BCI) for communication and motor control,” *Psychophysiology,* Vol. 43, no. 6, 2006.

[3] A. Dev, M. A. Rahman, N. Mamun, Antora Dev, “Design of an EEG-Based Brain Controlled Wheelchair for Quadriplegic Patients,” *Conference for Convergence in Technology (I2CT)*, 2018.

[4] J. L. Collinger, M. L. Boninger, T. M. Bruns, K. Curley, W. Wang, and D. J. Weber, “Functional priorities, assistive technology, and brain-computer interfaces after Spinal Cord Injury,” *The Journal of Rehabilitation Research and Development*, vol. 50, no. 2, p. 145, 2013.

[5] H. A. Lamti, M. M. Ben Khelifa, A. M. Alimi, and P. Gorce, “Influence of mental fatigue on P300 and SSVEP during virtual wheelchair navigation,” *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2014.

[6] X. Zhao, C. Liu, Z. Xu, L. Zhang, R. Zhang, “SSVEP Stimulus Layout Effect on Accuracy of Brain-Computer INterfaces in Augmented Reality Glasses,” *IEEE Access,* vol. 8, pp. 5990-5998, 2020.

[7] 24. O. Friman, I. Volosyak and A. Grser, "Multiple channel detection of steady-state visual evoked potentials for brain-computer interfaces", *IEEE Trans. Biomed. Eng*., vol. 54, no. 4, pp. 742-750, Apr. 2007.

[8] S. Li, J. Duan, Y. Sun, X. Sheng, X. Zhu, and J. Meng, “Exploring fatigue effects on performance variation of Intensive Brain–computer interface practice,” *Frontiers in Neuroscience*, vol. 15, 2021.

[9] A. Myrden and T. Chau, “Effects of user mental state on EEG-BCI Performance,” *Frontiers in Human Neuroscience*, vol. 9, 2015.

[10] Y. Zhang, S. Q. Xie, H. Wang, and Z. Zhang, “Data Analytics in steady-state visual evoked potential-based brain–computer interface: A Review,” *IEEE Sensors Journal*, vol. 21, no. 2, pp. 1124–1138, 2021.p

[11] J. Xie, G. Xu, J. Wang, M. Li, C. Han, and Y. Jia, “Effects of mental load and fatigue on steady-state evoked potential-based brain-computer interface tasks: A comparison of periodic flickering and motion-reversal based visual attention,” *PLOS ONE 2016.*

[12] M.-H. Lee, J. Williamson, Y.-E. Lee, and S.-W. Lee, “Mental fatigue in central-field and peripheral-field steady-state visually evoked potential and its effects on event-related potential responses,” *NeuroReport*, vol. 29, no. 15, pp. 1301–1308, 2018.

[13] A. Turnip, M. A. Suhendra, and Mada Sanjaya W. S., "Brain-controlled wheelchair based EEG-SSVEP signals classified by Nonlinear Adaptive Filter," *2015 IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2015.

[14] J. A. Wilson, J. Mellinger, G. Schalk, and J. Williams, "A procedure for measuring latencies in brain-computer interfaces," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 7, pp. 1785–1797, 2010.

[15] F. Dehais, A. Dupres, G. Di Flumeri, K. Verdiere, G. Borghini, F. Babiloni, and R. Roy, "Monitoring Pilot's cognitive fatigue with engagement features in simulated and actual flight conditions using a hybrid fNIRS-EEG passive BCI," *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2018.

[16] Y. Yan, Y. Xie, Y. Song, and Y. Liu, "The Effects of Weight on Comfort of Virtual Reality Devices," in Advances in Ergonomics in Design, K. Chen, Ed. pp. 239–248.

[17] "Mentalab Explore," *Mentalab,* 29-Mar-2023. [Online]. Available: https://mentalab.com/.

[18] A. Widyotriatmo, Suprijanto, and S. Andronicus, "A collaborative control of brain-computer interface and robotic wheelchair," *2015 10th Asian Control Conference (ASCC)*, 2015.

[19] J. Górecka, P. Makiewicz, "The Dependence of Electrode Impedance on the Number of Performed EEG Examinations" *Sensors*, vol. 19, no. 11, 2019.

[20] R. J. Barry, A. R.Clarke, S. J. Johnstone, C. A. Magee, J. A. Rushby, "EEG differences between eyes-closed and eyes-open resting conditions" *Clinical Neurophysiology*, Vol. 118, no. 12, pp. 2765-2773, 2007.

[21] R. H. Souza and E. L. Naves, "Attention detection in virtual environments using EEG signals: A scoping review," *Frontiers in Physiology*, vol. 12, 2021.

[22] A. Ravi, N. H. Beni, J. Manuel, and N. Jiang, "Comparing user-dependent and user-independent training of CNN for SSVEP BCI," *Journal of Neural Engineering*, vol. 17, no. 2, p. 026028, 2020.

[23] K. O'Keeffe, S. Hodder, A. Lloyd, "A comparison of methods used for inducing mental fatigue in performance research: individualized, dual-task and short duration cognitive tests are most effective" *Ergonomics*, pp.1 -12, 2020.

[24] S. K. Swee, L. Z. You, and K. T. Kiang, "Brainwave Controlled Electrical wheelchair," *MATEC Web of Conferences*, vol. 54, p. 03005, 2016.

[25] N. Erasala and D. C. Yen, "Bluetooth technology: A strategic analysis of its role in Global 3G Wireless Communication Era," *Computer Standards & Interfaces*, vol. 24, no. 3, pp. 193–206, 2002.

[26] R. Rondón, M. Gidlund, and K. Landernäs, "Evaluating bluetooth low energy suitability for time-critical industrial IOT applications," *International Journal of Wireless Information Networks*, vol. 24, no. 3, pp. 278–290, 2017.

[27] Y. Chen and M. J. DeVivo, “Epidemiology of Spinal Cord Injury,” *Spinal Cord Medicine*, 2018.

[28] R. S. Fisher, G. Harding, G. Erba, G. L. Barkley, and A. Wilkins, “Photic- and pattern-induced seizures: A review for the Epilepsy Foundation of America Working Group,” *Epilepsia*, vol. 46, no. 9, pp. 1426–1441, Sep. 2005.

[29] M.-H. Lee, J. Williamson, Y.-E. Lee, and S.-W. Lee, “Mental fatigue in central-field and peripheral-field steady-state visually evoked potential and its effects on event-related potential responses,” *NeuroReport*, vol. 29, no. 15, pp. 1301–1308, 2018.

[30] *Code of Federal Regulations Title 21*, Sec. 882.1400, U.S. Food & Drug Administration [Online]. Available: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfcfr/CFRSearch.cfm?fr=882.1400

[31] G. H. Klem, H. O. Lüders, H. H. Jasper, and C. Elger, “The ten twenty electrode system: International Federation of Societies for electroencephalography and clinical neurophysiology,” *American Journal of EEG Technology*, vol. 1, no. 1, pp. 13–19, 1961.

[32] N. Taguchi, S. Taguchi, S. Ishizuki, and H. Ito, “Contact dermatitis associated with the BISPECTRAL index™ sensor: A case report,” *JA Clinical Reports*, vol. 6, no. 1, 2020.