CALIFORNIA STATE UNIVERSITY, NORTHRIDGE

INTELLIGENT WHEELCHAIR UTILIZING A FUZZY APPROACH WITH COGNITIVE, FACIAL AND SPEECH INPUTS FOR USER COMMANDS

A thesis submitted in partial fulfillment of the requirements

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In Mechanical Engineering

By

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

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Creating tools and devices to provide ways to give independence to persons with disabilities is important. Everyone should have an opportunity to live as independently as possible and have a life filled with their own decisions and choices. Utilizing devices can alleviate some of the challenges for persons with limited mobility. In this case, a fuzzy logic controller was developed to dynamically control and interpret user commands to the motors of a powered wheelchair. This would assists the user into navigating their surroundings employing user commands via electroencephalography (EEG) signals, facial movements, and vocal inputs.

Human subjects participated in a study. In this particular investigation, the results are from individuals with no physical and cognitive disabilities. Subjects that participated utilized the user commands mentioned previously in order to maneuver through an obstacle course to meet a particular objective. The course was completed using different modes of motion control: a manual mode, a hybrid mode, and a hybrid mode combined with the fuzzy logic controller. The manual mode was used as a baseline as there is no machine

intervention from path planning algorithms or fuzzy logic interpretation. These different modes were compared based on successfulness of completion, time duration to complete the objective, number of collisions encountered, and distances travelled but not be limited to these comparison in results. Using the results from the study, the user commands and controller were evaluated and rated on various criteria.

1.0 INTRODUCTION

In general, BCI systems consists of a device that acquires signals from the brain which can be used to manipulate an external device or end effector. Conceptually, this is easier said than done. BCI technology is still very challenging. For users, that still have ability to move, this technology is almost unnecessary. Individuals with limited mobility would benefit more with this technology, but it would still provide a challenging method of communication.

BCI Wheelchair graduate project aims to provide an intelligent powered wheelchair for individuals with limited mobility that require hands-free methods to interact with their wheelchair. This graduate project is part of the Mechanical Engineering Department at California State University, Northridge. This is an important project because, no matter who you are, each person deserves to live the way they choose and use tools like these can give more possibilities to live independently. There should be options for individuals with limited mobility and the availability for the customization of tools and devices so that each person's needs can be approached on an individual level instead of a one size fits all concept.

To alleviate the challenges of BCI technology for the users, a shared control was considered where the powered wheelchair will autonomously make decisions on its motion control and be aided by the user with hybrid modes of user commands in combination with cognitive, facial, and speech commands. In addition, a fuzzy logic interpreter will determine the users intended direction based on the intent of the command and levels of likeness of that command. A human study was administered to compare these different modes and create a rating system of the commands used as well as compare different shared control modes. This rating system should create a way for wheelchair users to find the mode easiest for them to interact with their powered wheelchair. In addition, the developed controller can increase intelligence of the wheelchair to create a more reliable way for users to interact with their machines more naturally and with little effort.

2.0 BACKGROUND

2.1 Brain Computer Interface Systems Background

Imagine for a moment that you could control things or machines with only your thoughts. This idea can be seen in science fiction, games, toys, and movies such as *Avatar*, where a paraplegic soldier interfaces with an "avatar", which is an external bioengineered alien version of himself that is controlled by his brain. Another example is *The Matrix*, where human beings unknowingly interact with and are trapped in an alternative virtual reality, which their minds are plugged into. Star Wars Science created a mind trick game and toy called the Jedi Force Trainer, where the user using a headset can move a ping pong sized object up and down using their mind. These are examples of Brain Compute Interface (BCI) systems in popular culture. BCI technology is not a new idea. It has been around but only until now has it had some further movements in its development.

In the simplest form, "… BCI systems measure specific features of brain activity and translate them into device control signals (Schalk, et al., 1034)." In a basic BCI systems consist of at least the following elements: 1. A device that acquires brain activity from a subject in a form at which a compute or controller can understand, 2. Brain activity signals are processed by the computer and interprets the features from the signal based on a set of algorithms and logic, 3. The translated brain activity gets converted into an action per the subject's request, and 4. Some form of user feedback for the subject's verification.

2.1.1 Data Acquisition

There are 2 common methods of acquiring the brain activity signals: Noninvasive and Invasive. Noninvasive data acquisition are typically acquired by placing electrodes over the surface of the scalp in specific regions of interest. Invasive data acquisition are more intrusive requiring surgery and data is collected by carefully implanting electrodes in or on the surface of the brain.

The intelligent powered wheelchair, discussed in a later passage, is using a noninvasive type of Electroencephalography (EEG) technology. The noninvasive device will be used to "measures differences in the electrical potential between two locations on the scalp, which are produced by the changing electrical activity of the neurons in the brain (Burdet, et al, 12)".

2.1.1.1 Electroencephalography

BCI systems are found commonly using EEG as the method of monitoring the brain activity. EEG is a measurement of electrical activity of the brain which is collected via electrodes and measured in terms of electrical potential as voltage, and it resembles fluctuating waves or more complex patterns. EEG is currently being used for diagnosis of neurological disorders and the creation of computerized tomography (such as a CT scan) that can be read to indicate altered mental status, head trauma, and much more. Other applications of EEG are used for brain electrical activity mapping, evoked potentials, and other neurodiagnostic tests. For this discussion EEG is used for a BCI system for users to interact with a machine.

2.1.2 Signal Processing

Recorded brain activity have features that can be extracted which could be used to determine the subject's intent. There are many features seen in the signal such "features or signals that have been used [in the past] include slow cortical potentials, P300 evoked potentials, sensorimotor rhythms recorded from the cortex, and neuronal action potentials recorded within the cortex (Cook and Polgar, 246)," but not limited to these.

2.1.3 User Application and Feedback

Features can be extracted and an algorithm or a set of algorithms can be used to translate these features to commands that a machine can do. Typically, there would be a feedback for the subject or user. Feedbacks depend on the application, could either be visual or tactical.

2.1.4 Other Works

Some applications and research of BCI systems are as follows:

- EEG into Cursor Movements (Fabiani, et al.)
- EEG as reward signals for Reinforcement Learning (Iturrate, Montesano and Minguez)
- Noninvasive brain actuated wheelchair relying on P300 neurophysiological protocol and automated navigation (Iturrate, et al.)

2.2 Current Wheelchair Project under Investigation

The current BCI wheelchair under investigation is the Brain Computer Interface Wheelchair graduate project at California State University, Northridge. This project aims to make an autonomous powered wheelchair utilizing mental commands, facial gestures, and speech recognition as mechanisms for the users to interact with the motion control of the wheelchair. The autonomous mode of the wheelchair is where the motion of the wheelchair is decided by the computer to navigate the surroundings. The concept of radial path planning is used as the base of the motion control of this vehicle. There are other features for terrain detection, to select preferred surfaces to travel across, obstacle avoidance, and outdoor navigation.

The current wheelchair used for this investigation has the ability to navigate paths and avoid obstacles using a radial polar histogram (RPH) algorithm which is based on the radial path planning concept. This wheelchair can also travel to predefined locations without user inputs using an outdoor navigation algorithm. It incorporates a hybrid BCI system where the inputs are from the brain activity, facial movements, and/or speech commands from the subject, and based on the surrounding area. This hybrid BCI wheelchair is meant for "persons with limited use of their legs and arms such as amputees or quadriplegics (Lin, et al., 316)." Users can interact with the wheelchair by changing the direction of motion and stopping and starting motion. These commands are translated based on a fuzzy logic controller that will interpret the commands themselves. The fuzzy logic controller, also referred to as the fuzzy logic interpreter, is based on the intent of the user from the EEG signals, vocal inputs, and objects nearby. Any combination of the following methods can be used to create commands for the intelligent powered wheelchair: cognitive commands, facial gesturing commands, and speech commands. These features allow the user to have full control or allow autonomy of motion of the powered wheelchair without the need to physically interact with it. An overview of the system can be seen in Figure 1.

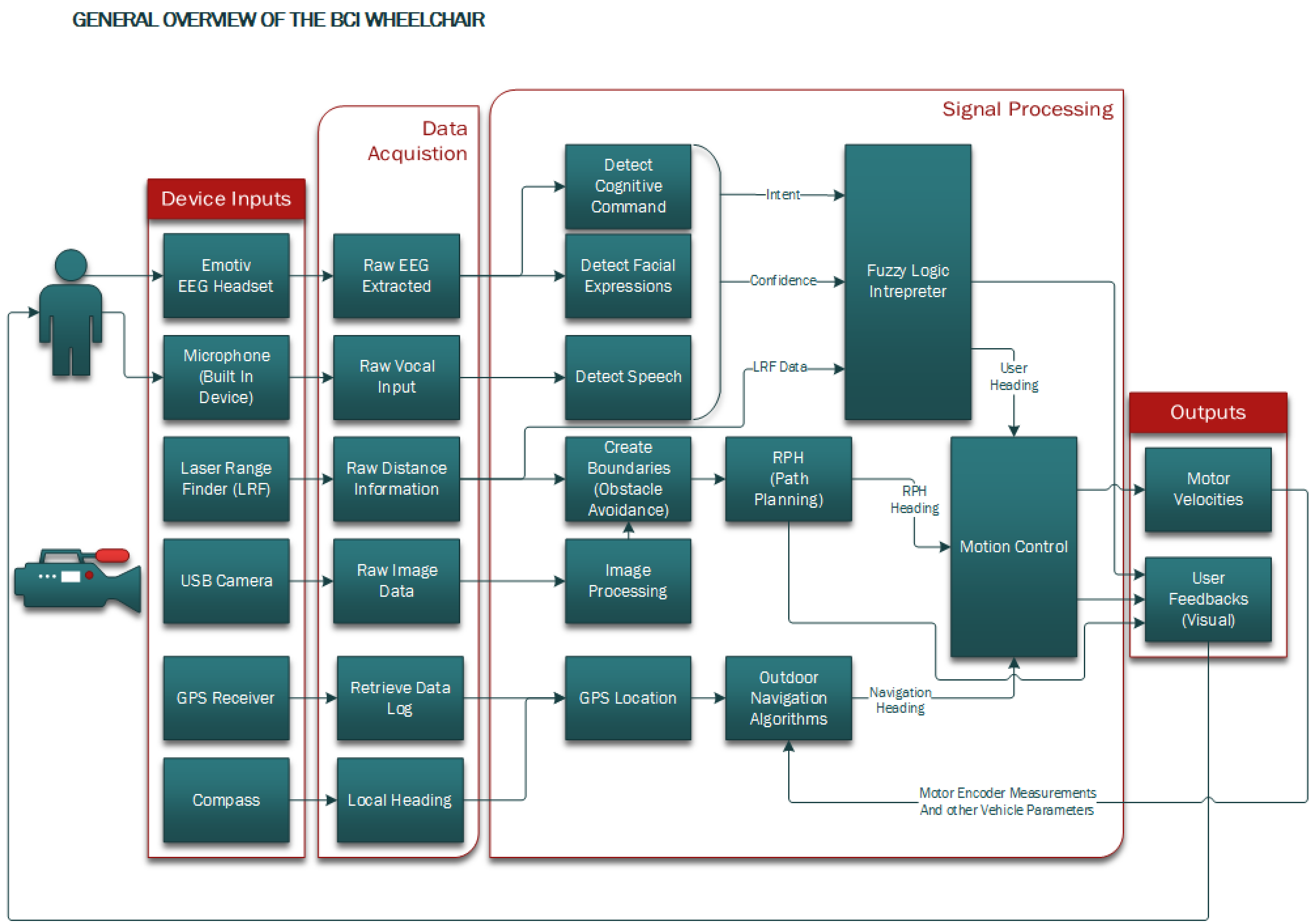


Figure 1: Flowchart of BCI Wheelchair System

2.3 User Inputs

The wheelchair would not be called a BCI system without interfacing with the brain. This is where the user inputs come into play. The following are the user inputs that are used to interface with the intelligent wheelchair:

- Cognitive commands using brain activity
- Facial commands using facial expressions and gestures
- Speech commands interpreted by speech recognition software

2.3.1 Cognitive Commands via EEG

The user trains cognitive commands through the software interface collecting samples from the raw EEG, brain activity sample, and through a series of pattern recognition and machine learning algorithms. Historically, BCI systems used P300, other event evoked potentials, or motor imagery, but not limited to these stimuli, to cognitively interface with machines. According to the developer of the EEG headset used, those responses are not considered (gmac 2013). Pattern recognition and machine learning algorithms proprietary to the company are processing the EEG which neglects artifacts due to muscle movements (gmac 2013), refer to 3.1.1 for the discussion of the EEG headset used.

There are many difficulties using EEG. One of the challenges is achieving consistency from the users for their cognitive commands. It isn't an everyday task to create consistent cognitive thoughts, and there are not a lot of home use products on the market that use a brain computer interface. "When using the EEG as a clinical tool, one should always keep in mind that the EEG recording is simply a random sample of the person's brain electric activity taken at a particular period of time" (Duffy, Iyer and Surwillo 1989).

If the brain activity isn't captured at the moment when the user is training a sample for command recognition, then the sample itself wouldn't necessarily mean anything, as it would just be a random occurrence of brain activity.

Even if the user were able to train the machine to understand their mental commands, another problem occurs due to feedback lag. For example, if the user creates a mental command, then that action may not activate immediately. Techniques used for motion control of a BCI system that interacts with a robotic arm found that "a major issue in describing motor control is the problem of integrating the one-way input-output processing involved in neural information for motion planning and execution with the two-way energy exchange that characterizes interaction…with the environment and delayed neural feedback" (Burdet, Franklin and Milner, 5).

2.3.2 Facial Commands via EMG

There are three common artifacts seen in EEG: 1. Heart pulses which are recorded in an electrocardiogram (ECG), 2. Muscle movements, which are recorded in an electromyogram (EMG), 3. Eye movements, which are recorded in an electrooculogram (EOG). Facial commands are generated by the user through movement of the face creating common facial expressions such as smiling, blinking, and even laughter utilizing the EMG artifact, and eye movement direction such as looking left or looking right utilizing the EOG artifact in the live EEG recordings from the users. Gestures like these can be associated to different actions the machine can understand.

2.3.3 Speech

Speech commands are made by the user verbally creating a series of words that correlate to an action. Similar to hands-free setting on cell phones to make calls, read text messages, or navigate with the built in GPS.

2.4 Fuzzy Logic Background

Fuzzy logic is a line of reasoning based on truth values that vary between 0 and 1. Compared to the classical logic or Boolean logic where these truth values are only "True" or "False," 1 or 0, fuzzy logic can address a range of values for partial truths, which aren't completely true or completely false. This definition is considered the narrow sense or micro scale view of fuzzy logic. Fuzzy logic can also be defined in a board sense as "all of the theories and technologies that employ fuzzy sets, which are classes with unsharp boundaries" (Yen and Langari 1999, 3). The design of the fuzzy logic interpreter, discussed in Section 3.2, uses the board sense of the concept.

Fuzzy logic applications are decision-making support, pre-diagnostic and inquiry system, medical diagnosis, databases, scheduling, speech recognition, automotive speed control (Terano, Asai and Sugeno 1994), rice cookers, washing machines, and toilets. For this design, fuzzy logic will be used to interpret the users' intent and convert it to a local heading that the powered wheelchair can use to govern its motion control.

The following passages are some of the fuzzy logic concepts that will be considered for the fuzzy system design which are fuzzy sets and their membership functions, linguistic variables, fuzzy rules, and defuzzification.

2.4.1 Fuzzy Sets and Membership Functions

A fuzzy set is a set of values that vary between 0 and 1 or a set of values with degrees of membership. Fuzzy sets are special because they can be used in a combination with other techniques and in terms of natural language. For example, to determine when the air condition is turned on or turned off based on if it is hot, warm, or cold and/or very hot, slightly hot, or not so hot. “Fuzzy sets are a mathematical method that [were] invented with the goal of expressing the semantic ambiguity in human language, and they are unique in that they make it possible to deal scientifically with subjectivity” (Terano, Asai and Sugeno 1994, 6).

Fuzzy sets “contain objects that satisfy imprecise properties of membership… [and where boundaries]…of the fuzzy sets are vague and ambiguous. (Ross 1995, 10-11)” Membership functions are “function[s] that maps objects in a domain of concern to their membership value in the set… [and]...provides a gradual transition from regions completely outside a set to regions completely in the set” (Yen and Langari 1999, 29). Fuzzy sets are at times considered not well-defined as classical sets, or crisp sets, but despite the notion of the ambiguity of the fuzzy set, they can be defined clearly with the use of a membership function where the elements of the set lies between 0 and 1. They are considered “fuzzy” because they aren’t strictly defined as a unique value of either off or on, or false or true, since they can vary between 0 and 1. Fuzzy sets have infinite possibilities so their membership function can also have infinite variations. “The most commonly used in practice are triangles, trapezoids, bell curves, Gaussian, and sigmoidal functions” (Yen and Langari 1999, 25).

2.4.2 Linguistic Variables

Linguistic variables are both a description in linguistic terms and qualitatively as a membership function. These linguistic terms are descriptions of the variable in words commonly used in normal day to day conversation like tall, short, heavy, light, loud, soft, etc… "A linguistic variable is like a composition of a symbolic variable (a variable whose value is a symbol) and a numeric variable (a variable whose value is a number)" (Yen and Langari 1999, 31).

2.4.3 Fuzzy Rules

Once linguistic variables are determined they can be used in combination with fuzzy if-then rules, fuzzy rules; normally determined by experts or through observations. These fuzzy rules in this instance are conditional statements; IF "this" THEN "that". "[This] fuzzy implication…, is known as the generalized *modus ponens* form of inference" (Ross 1995, 269). In the if-then rule, the "this" is an antecedent, premise or condition, and the "that" is a consequent, conclusion as a result of the antecedent. These rules are used in a knowledge base in fuzzy systems.

2.4.4 Defuzzification

Using these concepts and other techniques, defuzzification can be implemented. In fuzzy systems, inputs can be discrete values that become fuzzified. "Fuzzification is the process of making crisp quantity fuzzy" (Ross 1995). Basically, the discrete values is turned into a degree of membership of the fuzzy set(s) so that they are in terms of fuzzy value. Defuzzification is the opposite of fuzzification. Defuzzification is used when a discrete value is desired.

3.0 INTEGRATION OF USER INPUTS

This passage will discuss the method of communication the user can employ to interact with the intelligent powered wheelchair. These methods, user inputs, will be used to interpret the heading the wheelchair should take. There are 4 user commands (forward, left, right, and stop) that can be used in any combination of the 3 different methods (cognitive, facial, and speech). The heading is referring to the local heading of the wheelchair, this direction is in terms of degrees where the immediate right is 0° and to the left is 180°, refer to Figure 2. The heading will be determined based on the output of a fuzzy logic interpreter. The fuzzy logic interpreter takes multiple inputs i.e. the user inputs (intent and confidence) and surrounding obstacles. It also uses fuzzy techniques in combination with the fuzzy rules, and implication, refer to section 2.4, so that a discrete value can be obtained for the local heading of the wheelchair. This fuzzy logic interpreter will be discussed in more detail in section 3.2.

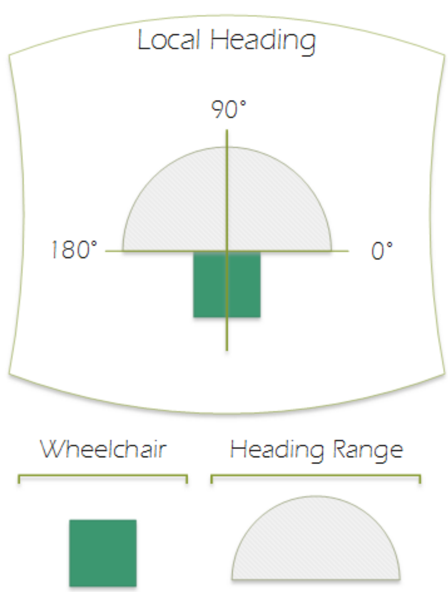


Figure 2: Heading Orientation*

*The image on the left is the local heading of the wheelchair. The image on the right is the coordinate system the fuzzy logic interpreter uses but will output the user heading based on the local heading coordinate system.

3.1 User Inputs

The user or subject can use one or a combination of the following commands to interact with the intelligent powered wheelchair: cognitive (using mental thoughts), facial (using facial gestures), and speech (using the voice). Each command can provide the direction: forward, left, right, and stop; and magnitude of the direction: slight, medium, and wide, or no change, “normal” turn, and large turn. The terminology will depend on what type of command is used. The software will determine what is appropriate. The software is created in LabVIEW and utilizes Software Development Kits from Emotiv to detect cognitive and facial expressions for cognitive and facial commands, and Microsoft Speech Recognition to detect speech inputs for speech commands. The following will discuss in more detail what commands can be made.

3.1.1 Cognitive Commands

Cognitive commands are interpreted using an Emotiv EEG headset and the Emotiv Research Edition Software Development Kit (SDK). The EEG headset used has 14 channels along the scalp. This headset was designed for the gaming industry. Despite their target audience, plenty of researchers have used this headset for BCI systems. The headset is compact, easy to set up, aesthetically pleasing, and compatible for this real-time application. The “Cognitiv” Suite can take mental commands generated by the user, and the suite’s algorithm interprets the brain activity and associates it to 13 cognitive actions (push, pull, lift, drop, left, right, rotate left, rotate right, rotate clockwise, rotate counter clockwise, rotate forwards, rotate reverse, and disappear).

Each cognitive action has a direct influence on a cube generated on the screen, so if the cognitive action was a push, then the cube would be pushed forward. This action doesn’t necessarily have to be the same as the mental thought that the user wants to create to generate the action. These thoughts could be one or more of the following (but not limited to this list):

- A color or colors
- A figure
- A mental event or task
- A mental task added with a physical task like making a fist
- Multiple things like sounds, visual images, and patterns rehearsed in the mind.

The subjects were given the freedom to choice their thoughts. Refer to section 5.0 on the thoughts used by the subjects.

The original concept was to only use cognitive commands. Many users find it challenging to create more than one or two cognitive commands. So multimodal commands were considered, where the user could choose different combinations of commands that were easiest for them to do.

Using the Emotiv Cognitiv Suite demo software, limited the users to 4 cognitive actions could be used at once. Emotiv claims that, “increasing the number of concurrent actions increases the difficulty in maintaining conscious control over the Cognitiv detection results (Emotiv, 31).” The software for the wheelchair does not put a limit but since there are currently only 4 commands a user can make, 4 cognitive commands can be used if an experienced user is able to manage them.

An example of a command a user would use is to mentally visualize an event such as pushing a box. This would be associated to a cognitive action such as “push”. To associate this action, the software needs to sample brain activity while the user is creating the mental command. To train a cognitive command, multiple 8 second samples of brain activity are collected. This will serve as a training set for the software to detect features in the brain signal to determine the intent of the subject. Each detected command has an action power. The action power is the defined as the likeliness that it was the intended command. The detected command and this likeliness value will be used by the fuzzy logic interpreter.

3.1.2 Facial Gestures

Facial commands are generated by the user by moving facial muscles to perform gestures or expressions. The Emotiv Expressiv Suite can detect facial expressions such as blinking, left and right winking, raising and furrowing one’s eyebrow, smiling, clenching of the teeth, laughter, and left and right smirking. The Emotiv SDK has a universal signature, a profile that works with most people. In the case this universal signature does not recognize the user’s facial expressions as well, each subject has the opportunity to train specific facial expressions. Signals are taken from the EEG, recall that EMG is an artifact that appears in recorded EEG. Similar to cognitive training, facial expressions are collected from EEG signals through the headset. The Emotiv headset can detect eye movement as well, recall that EOG is an artifact of EEG and has a unique pattern so that feature can be detected. This could be paired to a command, but since the user has to use their eyes to visually detect obstacles in the path of the wheelchair it would not be desirable to use them as inputs. For example, the user must move their eyes to look over an obstacle but if eye movements were a command, it would consider this as an input and travel towards the obstacle instead of avoiding it. The following is a list of facial expressions that users will select to be associated to a command: left and right wink, raise and furrow eyebrows, clench, and left and right smirk. Using the universal signature or the unique, trained signature for the user, the facial expression will be detected and the software will assign an intent. Each detection will also have an action power similar to the cognitive action power which is a value of the likeliness of that particular gesture. The action power and the intent will be sent to the fuzzy logic interpreter.

The Expressiv Suite has other expressions that will not be considered for user commands such as blinking, looking left or right, smiling and laughter. These were not used because it will continually poll for these actions, and the software cannot judge without help if a particular expression is intended or involuntary.

3.1.3 Speech Commands

Speech commands are detected using Microsoft speech recognition and the built-in microphone of the laptop. A grammar list is created with words that will be detected by the speech recognition software. These words will be used to create speech commands.

Grammar List:

1. Listen
2. Forward
3. Left
4. Right
5. Stop
6. Slight
7. Medium
8. Wide
9. Cancel

The speech commands are structured differently than the cognitive and facial commands. Speech has 3 phases: 1. Listening, 2. Direction, and 3. Magnitude.

The listening phase is when the user gets the attention of the software to start detecting speech commands. This phase is a hotkey for the software to know that the user intends to create a speech command. The reason this was implemented was to prevent false commands when the user is speaking casually without the intent of creating a command. Once the software detects that the user intends to create a command, the wheelchair will stop moving and the speech command will go into the next phase, the direction phase.

The direction phase is where the user will give the different commands such as forward, left, right and stop. The forward command lets the wheelchair know to move forward. This ends the speech command and the magnitude phase is skipped. Left or right commands will set the wheelchair to make a left or right turn, and then it will go into the magnitude phase where the user can determine the desired region. Stop will turn off the autonomous mode, will prevent the wheelchair from continuing to move, and will not go into the magnitude phase.

The magnitude phase is only meant for making turns. It allows the user to determine approximately how much to turn. After setting the magnitude it will complete the speech command and will output a heading and intent for the fuzzy logic interpreter. Unlike cognitive and facial commands there is no likeliness value so instead a discrete heading will be sent to the interpreter and converted to a percentage. The user can select a slight, medium, or wide turn. The behavior of the turn is based on the membership functions of each magnitude, refer to section 3.2.1, and the motion control will determine the speeds of each wheel based on the heading computed by the fuzzy logic controller.

The “cancel” phrase will cancel the command and go back into the autonomous mode. The user can cancel in any part of the phases except if the speech command was completed in all its phases, which happens after setting a magnitude for the turns or setting a forward or stop command in the direction phase.

When the listening phase is actuated the computer will output an audio feedback for the user to know what the computer has heard. For example, if a user wanted to create a slight right turn, the following would occur:

User: "Listen"
The wheelchair will stop moving
Computer: "Listening. What is your command?"
User: "Right"
Computer: "Making a right turn. How far Right?"
User: "Slight"
Computer: "Making a slight turn"
Ends the speech command and the wheelchair would proceed to make the turn.

Other Examples of Speech Command Word Combinations:

- Listen → Left →Wide
- Listen → Stop
- Listen → Forward
- Listen → Right→Medium
- Listen → Cancel
- Listen → Left → Cancel

3.1.4 Order of Priority

Since the user inputs could be any combination of different methods it is important to note the priority the commands. If a speech command is detected, it will override any cognitive or facial commands. If a facial command is detected without a speech command, the facial command will override any cognitive command. If a cognitive command is detected, it will only be used if no other method is detected. The priority is as such: 1. Speech, 2. Facial, and 3. Cognitive, refer to the flowchart in Figure 3.

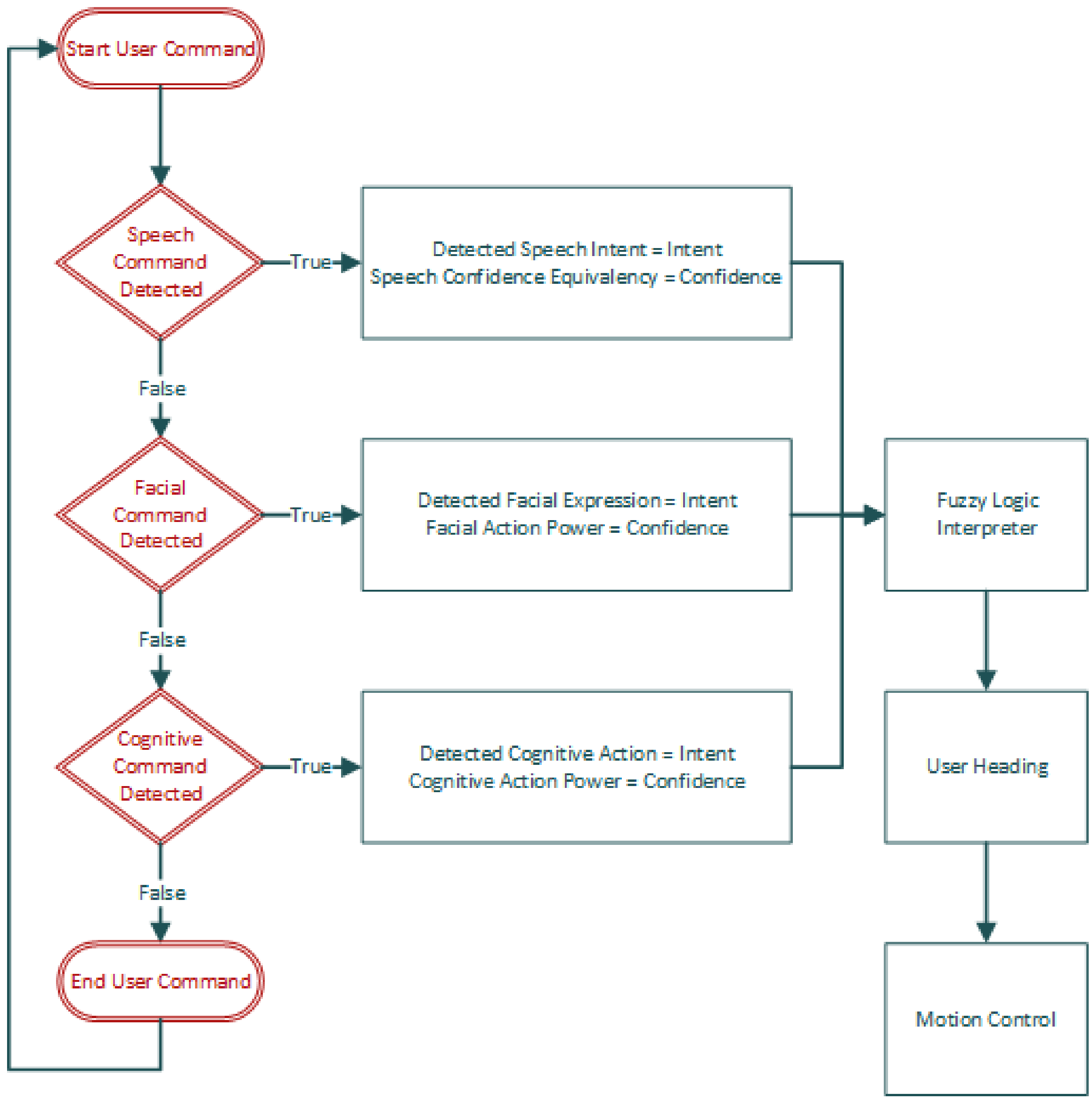


Figure 3: Command Priority Flowchart

3.2 Fuzzy Logic Interpreter

Sending multiple cognitive commands is challenging especially for new users. It also can be overwhelming for users because once in a mental state of frustration, it does not matter your level of experience, the cognitive detection may not interpret your intended signals. This can give false positives on commands that the user may not want to send. A fuzzy logic controller was designed and added between the user inputs and the motion control to possibly alleviate the user by lower their frustration and establish a better sense of communication to the machine. Let us call this fuzzy logic controller a fuzzy logic interpreter. This will convert the user inputs and translate them to something the machine can understand as a user heading, refer to Figure 4. The heading convention is different in the fuzzy logic interpreter than the local heading of the wheelchair for symmetry purposes, refer to Figure 5.

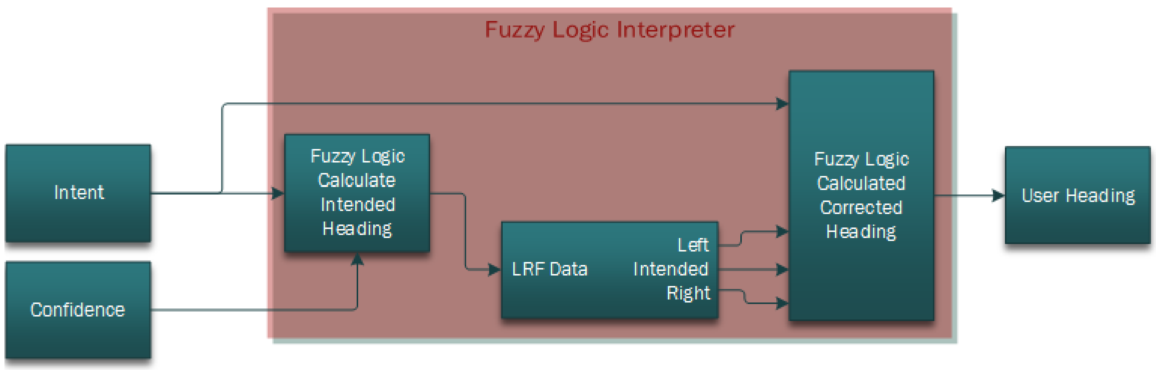


Figure 4: Overview of Fuzzy Logic Interpreter

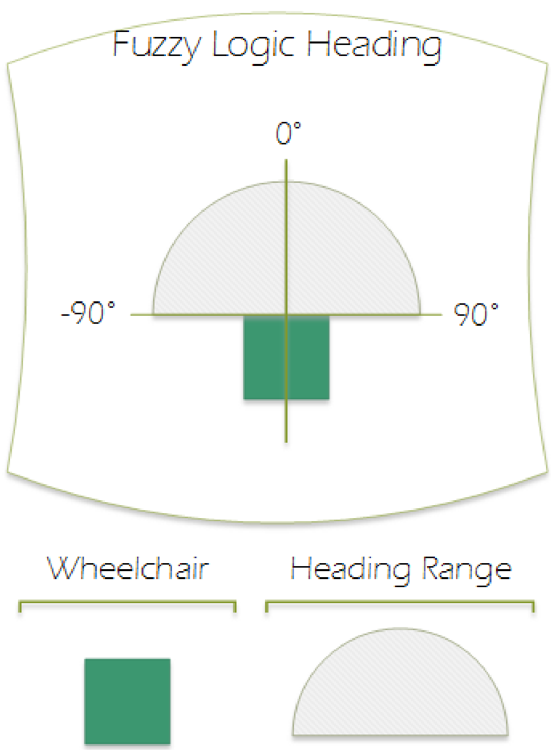


Figure 5: Fuzzy Logic Heading Convention

The fuzzy logic interpreter takes in multiple inputs and has a single output. The multiple inputs consist of the user command which has 2 components (detected action and confidence level) and obstacle detection at 3 specific regions from the laser range finder (LRF) collected data. The final output is the "user heading" which refers to the local heading or the direction the wheelchair will move towards. There are two fuzzy systems that will be used to do this. The first one is used to take the intent and confidence values and determine the intended heading. The intended heading will be used to locate the 3 specific points on the LRF data which will give distances of obstacles from the wheelchair. These distances and the intent (same as the intent sent to the first fuzzy system) will be sent to the second fuzzy system. This fuzzy system is based on an obstacle avoidance fuzzy logic controller. The second fuzzy system determines a value to correct the heading, by either adding or subtracting from the intended heading. This corrected heading will be the user heading that is sent to the motion control. Refer to the following passages on the design of these fuzzy systems.

Refer to the APPENDIX A and APPENDIX B for the inputs and output variables, and rules used in designing the fuzzy systems to interpret the Intending Heading and Corrected Heading, respectively, utilizing the Fuzzy Logic Toolkit in LabVIEW. Note some of the terminology is different from this current discussion for ease of understanding.

3.2.1 User Intended Heading

Using fuzzy logic, a fuzzy system was designed to interpret the discrete heading value that is sent to the motion control so that the vehicle speed can be determined. This fuzzy system takes the user input as the intended direction in terms of forward, left, and right, and the level of the likeness of the command such as action power from Cognitv and

Expressiv detection suites. Speech commands are detected with a confidence value, but due to the multiple parts of the command, a value is set based on the command made.

The input variables for this fuzzy system is defined as “Intent” and “Confidence”. Detected commands like Forward, Left, and Right are represented as singleton membership functions. These actions are assigned a value between 0-4 for the purpose of the software to distinguish between these actions. They are defined using Table 1 and Figure 6.

Table 1: "Intent" Membership Definition

Membership Function	**Shape**	**Range Value**
Forward	Singleton	1
Left	Singleton	2
Right	Singleton	3

The membership function can be illustrated as the following:

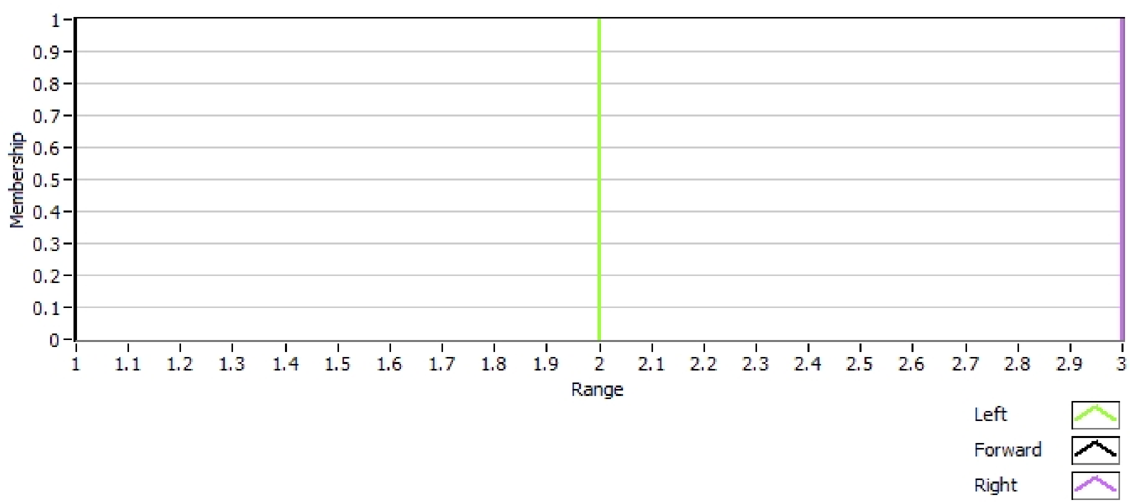


Figure 6: Membership Functions of the "Intent" Variable for Intended Heading

This input variable acts like a Boolean or a crisp value because only one command can be detected at a time. If the detected intent is Left, it cannot also be a detected intent of Right. The intent can only be one or the other, it will never be 2 or more of these intents.

For a stop command, the detected command will bypass the fuzzy systems and go directly to motion control to stop the wheelchair from moving.

The input variable called “Confidence” varies between 0-100% and consists of 3 membership functions. The 3 membership functions are “Very Sure”, “Sure”, and “Not So Sure”. These are illustrated in Figure 7.

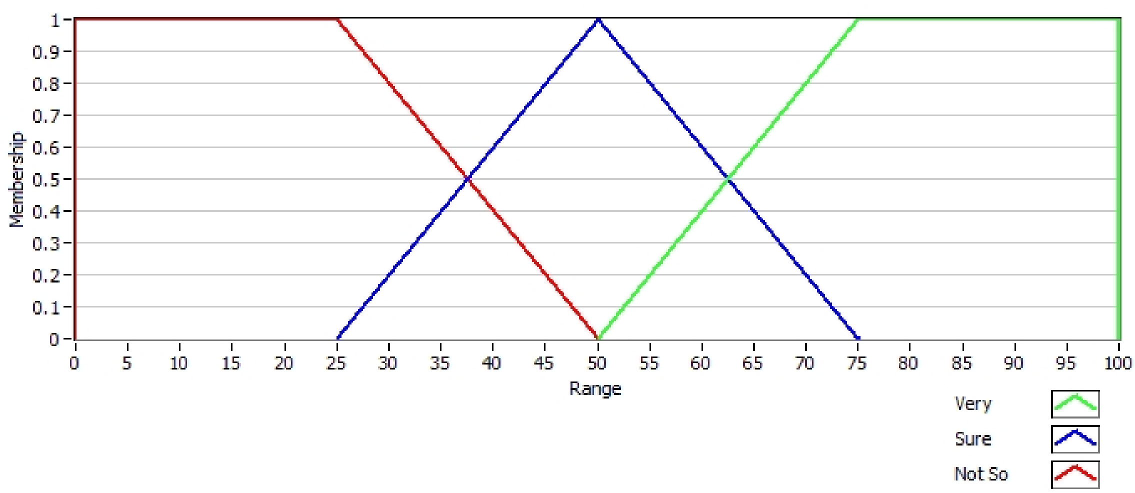


Figure 7: Membership Functions for the "Confidence" Variable

The membership function “Very Sure” is used when the confidence level of the detected intent is high; and very likely that was the detected command is the correct one. “Sure” is used when the detected command is more than likely correct. “Not So Sure” is used when the detected command is not likely to be correct.

The output variable for this fuzzy system is defined as “Intended Heading”. Intended Heading varies between -90° and 90°. It consists of 7 membership functions:

“Wide Left”, “Medium Left”, “Short Left”, “Forward”, “Short Right”, “Medium Right”, and “Wide Right”. Short, medium, and wide refers to the magnitude of the turn from small to large respectively. Refer to Figure 8 for the output membership functions for the Intended Heading.

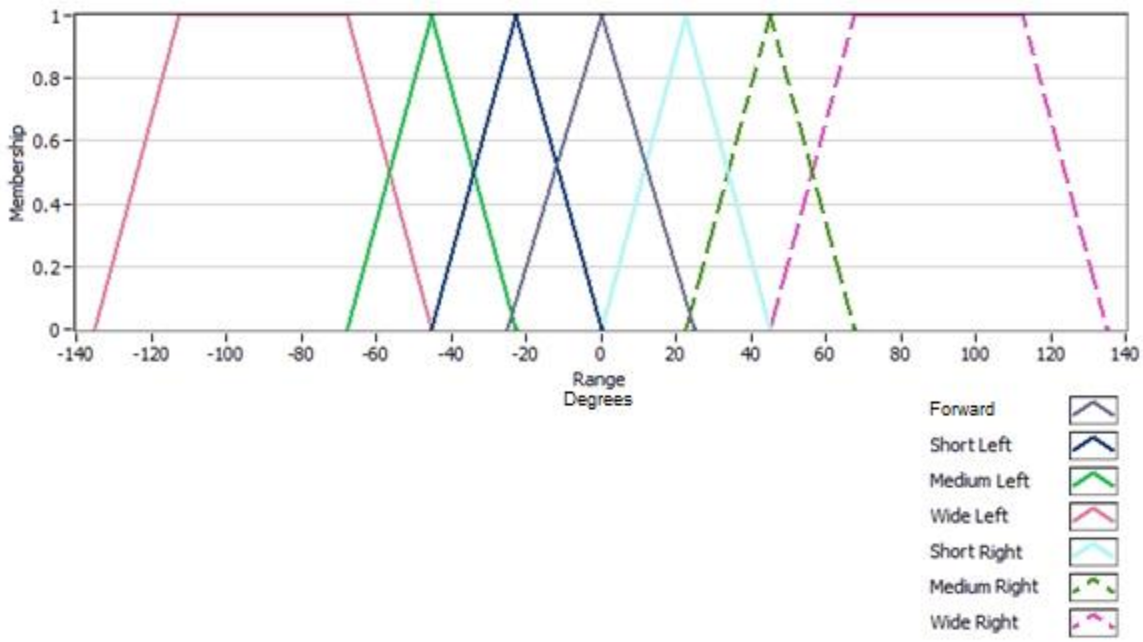


Figure 8: Output Membership Function for Intended Heading

The knowledge base consists of 9 fuzzy rules. The following are the fuzzy rules used:

Rule 1. **IF** 'Intent' IS 'Left' AND 'Confidence' IS 'Very Sure'
THEN 'Intended Heading' IS 'Wide Left'
Rule 2. **IF** 'Intent' IS 'Left' AND 'Confidence' IS 'Sure'
THEN 'Intended Heading' IS 'Medium Left'
Rule 3. **IF** 'Intent' IS 'Left' AND 'Confidence' IS 'Not So Sure'
THEN 'Intended Heading' IS 'Short Left'
Rule 4. **IF** 'Intent' IS 'Forward' AND 'Confidence' IS 'Very Sure'
THEN 'Intended Heading' IS 'Medium Forward'
Rule 5. **IF** 'Intent' IS 'Forward' AND 'Confidence' IS 'Sure'
THEN 'Intended Heading' IS 'Medium Forward'
Rule 6. **IF** 'Intent' IS 'Forward' AND 'Confidence' IS 'Not So Sure'
THEN 'Intended Heading' IS 'Medium Forward'
Rule 7. **IF** 'Intent' IS 'Right' AND 'Confidence' IS 'Very Sure'
THEN 'Intended Heading' IS 'Wide Right'
Rule 8. **IF** 'Intent' IS 'Right' AND 'Confidence' IS 'Sure'
THEN 'Intended Heading' IS 'Medium Right'
Rule 9. **IF** 'Intent' IS 'Right' AND 'Confidence' IS 'Not So Sure'
THEN 'Intended Heading' IS 'Short Right'

In summary, the rules can be visualized in Table 2.

Table 2: Rule Table for Intended Heading

Confidence / *Intent*	*Not So Sure*	*Sure*	*Very Sure*
Forward	Forward		
Left	Short Left	Medium Left	Wide Left
Right	Short Right	Medium Right	Wide Right
*Stop***	Stop		

**Stop is not in the Fuzzy Rules but if the intent is stop for any level of confidence, the vehicle should stop.

Various defuzzification techniques were simulated to narrow down which gave the best output based on prior experiences. The center of maximum (CoM) was selected to obtain a discrete value for the intended heading. This intended heading will be used for the next fuzzy system for determining the Corrected Heading which will be used as the User Heading for motion control.

3.2.2 Corrected Heading

The second fuzzy system will use observations of detected obstacles around the intended heading and determine whether the intended heading needs to be corrected. This fuzzy system is based on a fuzzy logic obstacle avoidance controller. For example, if the intent of the user was to go forward and the prior fuzzy system determined the heading to be 90° (directly in front of the wheelchair), and there are obstacles near the wheelchair in front and to the left, the fuzzy system would adjust the heading and make the wheelchair move more to the right instead of directly in front of the wheelchair. The reasons for this are for safety and to reduce collisions. If the user created the command in error, e.g. the user meant to make a right turn but triggered the forward command unintentionally, and an obstacle was directly in front of the wheelchair, this fuzzy system would change the heading either to turn left or right to avoid the obstacle.

Making a command in error occurs more often in crowded environments, dynamically changing environments, and surroundings with a lot of distractions. So this part of the fuzzy logic interpreter is a failsafe in the case that the user makes an unintentional command. This fuzzy system aims to reduce the user inputs in difficult situations. It handles situations where: 1. The user intends to turn but does not turn enough to avoid obstacles, 2. Identifies too many obstacles and attempts to turn around, and 3.

Does nothing if obstacles are close by. What it does not handle is if the operation detected the wrong command, as in the user intended to turn right but the software detected a left turn instead. The difference scenarios that can be addressed are illustrated in Figure 10.

There are 4 input variables for this fuzzy system: “Left”, “Intended”, “Right”, and “Intent”. Left, Intended, and Right refer to detected obstacles based on the intended heading. Intended is the distance of the detected obstacle located at the intended heading. Left and Right are the distances of the detected obstacles to the left and right of the intended heading. Left, Intended, and Right have 2 membership functions: “Near” and “Far”. Near and Far refer to obstacles that are either too close or far enough away. “Intent” is from the original detected intent and is the same linguistic variable from the previous fuzzy system, refer to Figure 6. The membership functions for Left, Intended, and Right have the same membership functions, refer to Figure 9, but the value taken is based on the obstacle detected in those 3 regions.

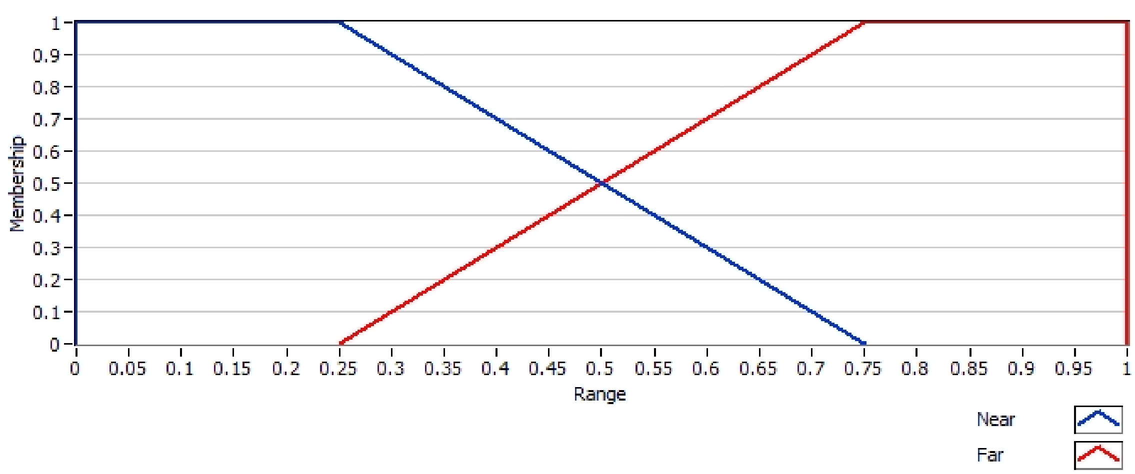


Figure 9: Membership Functions of Near and Far (Used for "Left", "Intended", and "Right" Input Variables)

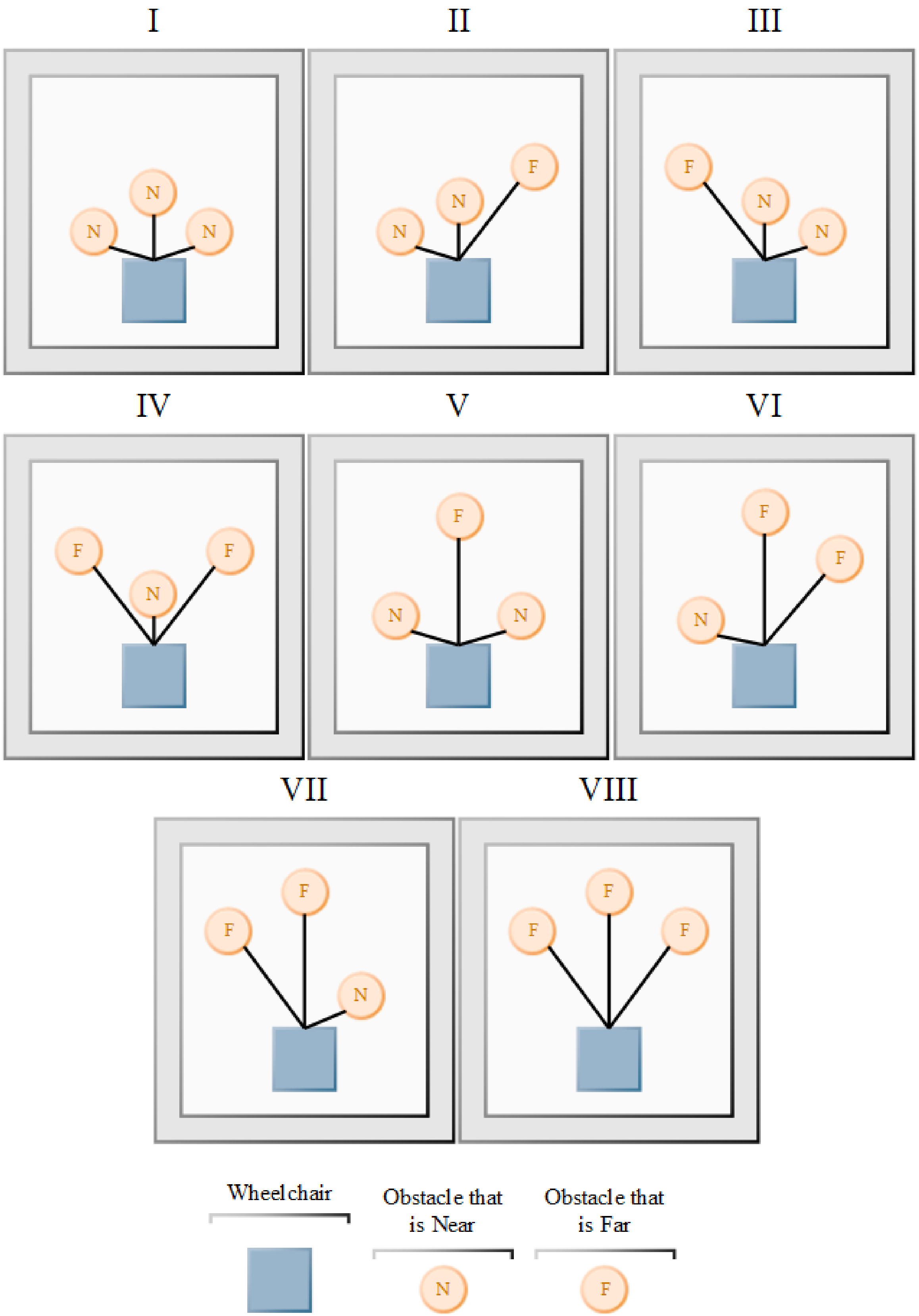


Figure 10: Scenarios of Detected Obstacles

The output variable for this fuzzy system is called “Corrected Heading” and contains 7 membership functions: “Large Left Turn”, “Turn More Left”, “Turn Left”, “No Change”, “Turn Right”, “Turn More Right”, and “Large Right Turn”. These membership functions refer to what should change in the intended heading. If turning left or right, it would subtract or add to the heading, respectively. The terms such as “Large”, “Turn More”, and “Turn”, refer, from largest to smallest respectively, to the magnitude of change applied to the heading. Refer to Figure 11 for the membership functions.

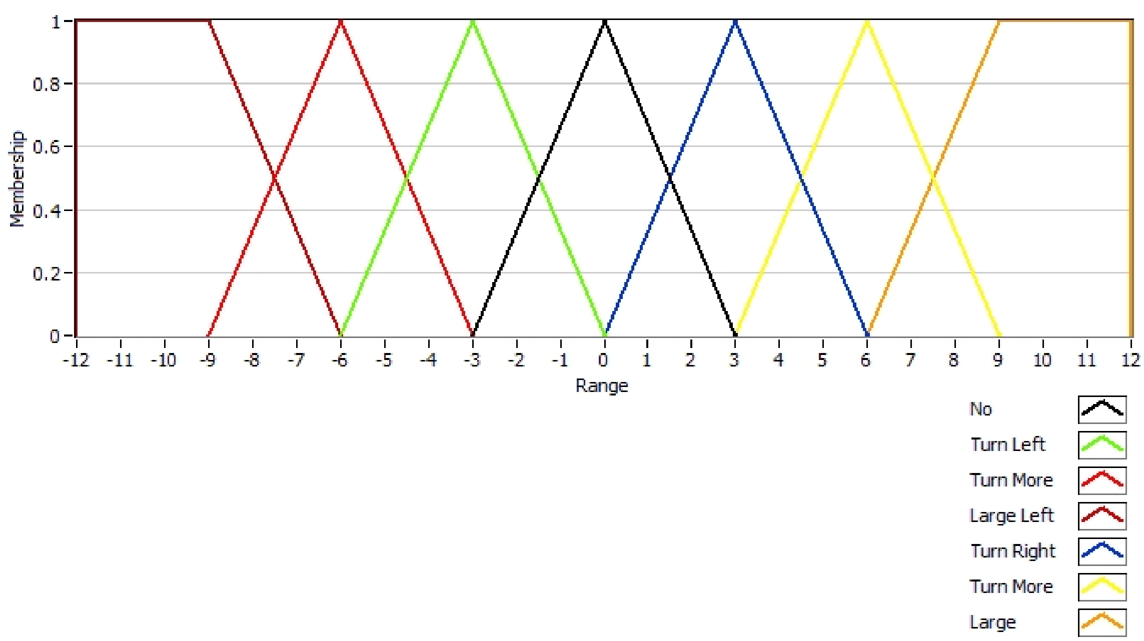


Figure 11: Membership Functions for the "Corrected Heading" Output Variable

Table 3 summarizes the fuzzy rules and the associated scenarios used for the knowledge base for this fuzzy system. The fuzzy operation for the IF-THEN rules is the conjunction (AND) which means that the rules would follow this format:

IF “Intended” IS <u>“Near/Far”</u> AND “Left” IS <u>“Near/Far”</u> AND “Right” IS <u>“Near/Far”</u> AND “Intent” IS <u>“Detected Command”</u>

THEN “Corrected Heading” IS <u>“Behavior”.</u>

Table 3: Fuzzy Rules for Calculating the Corrected Heading

Scenario	Rule	Intended	Left	Right	Intent	Behavior
	1	Near	Near	Near	Forward	Large Right Turn
I	2	Near	Near	Near	Left	Large Left Turn
	3	Near	Near	Near	Right	Large Right Turn
	4	Near	Near	Far	Forward	Turn More Right
II	5	Near	Near	Far	Left	Large Left Turn
	6	Near	Near	Far	Right	Turn Right
	7	Far	Near	Near	Forward	Turn More Left
III	8	Far	Near	Near	Left	Turn Left
	9	Far	Near	Near	Right	Large Right Turn
	10	Near	Far	Far	Forward	Turn More Right
IV	11	Near	Far	Far	Left	Turn More Left
	12	Near	Far	Far	Right	Turn More Right
	13	Far	Near	Near	Forward	No Change
V	14	Far	Near	Near	Left	Large Left Turn
	15	Far	Near	Near	Right	Large Right Turn
	16	Far	Near	Far	Forward	Turn Right
VI	17	Far	Near	Far	Left	Large Left Turn
	18	Far	Near	Far	Right	No Change
	19	Far	Far	Near	Forward	Turn Left
VII	20	Far	Far	Near	Left	No Change
	21	Far	Far	Near	Right	Large Right Turn
	22	Far	Far	Far	Forward	No Change
VIII	23	Far	Far	Far	Left	No Change
	24	Far	Far	Far	Right	No Change

Various defuzzification methods were simulated and it was determined that the CoM method gave the desired results. Using CoM, the Corrected Heading can be obtained as a discrete value. This value is set as the User Heading which is sent to motion control.

4.0 VALIDATION

The purpose of this study is to investigate alternative methods of interacting with an intelligent powered wheelchair and to determine if these methods are more beneficial. The lessons learned from this study could help define what is most effective for controlling an intelligent powered wheelchair BCI system via different hands free methods and between different combinations of shared control techniques.

Approval for this Human Subject Research was obtained to conduct this study through the Committee for Protection of Human Subjects at California State University, Northridge. The following passage will outline the subjection information, recruitment procedures, and experiment design and procedures.

4.1 Participants Considered

Upon approval of the human subject protocol, recruitment began. Flyers were distributed at the university with posting approval from the university and social media invitations were sent out via Facebook. Participants were selected based on the inclusion and exclusion criterion discussed on the next page. All participants were given an opportunity to read and understand the consent form and purpose of the study prior to signing the consent form.

Participants were selected based on the following inclusion and exclusion requirements submitted with the approved human subject protocol.

Inclusion Requirements:

- 18 years of age or older.
- Able to transfer them self into a standard size powered wheelchair.
- Able to speak.
- Do not have any perceptual impairments.
- Willing to be in contact with saline solution.
- Fall in either of the following categories:
    - You are a person with no cognitive and physical disabilities.
    - You are a person with physical disabilities which requires the use of a manual wheelchair or powered wheelchair.

Exclusion Requirements:

- If the Emotiv Electroencephalography (EEG) Headset:
    - Does not fit their head.
    - Is unable to establish a connection with the computer i.e. due to hair thickness.
- The participant is unable to view a computer screen or laptop screen set on a table while seated.

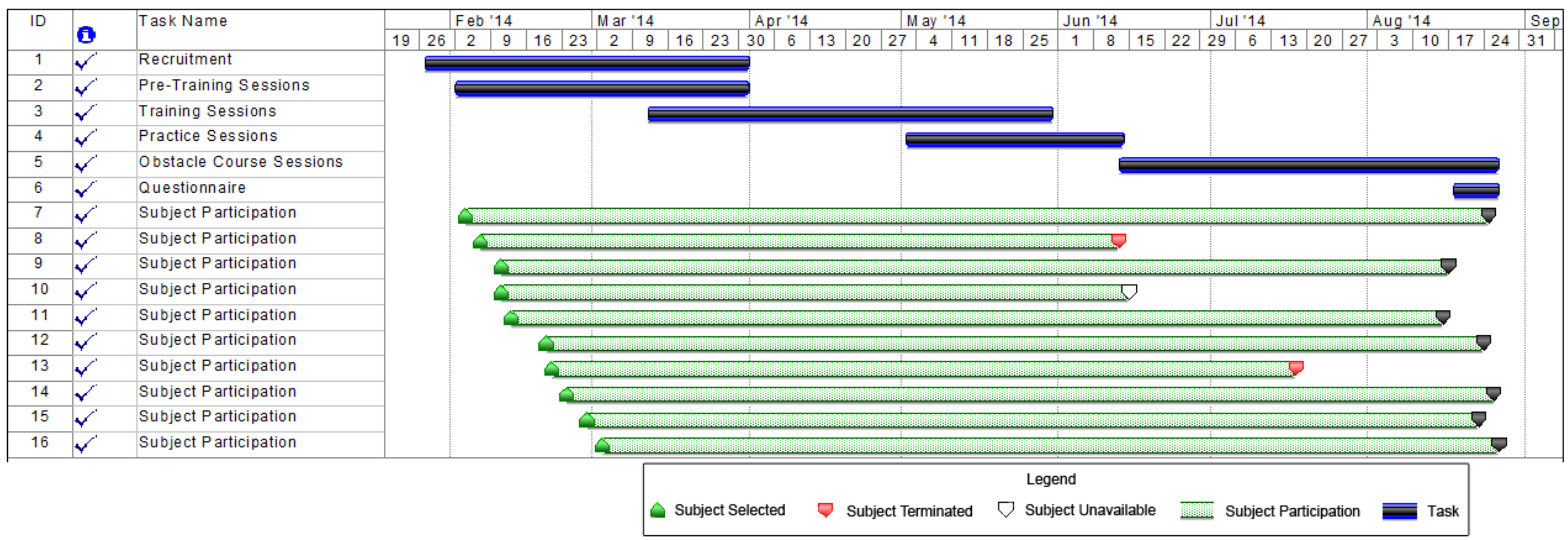


Figure 12: Participant and Study Timeline

Ten participants were selected and 7 of these participants were able to complete some obstacle sessions. Of the 7, there were 2 females and 5 males varying between the ages of 18-32. The other participants terminated their involvement or became unavailable prior to sessions in the obstacle course, refer to the timeline in Figure 12. They all had no prior experience using the intelligent powered wheelchair of interest or other BCI systems.

4.2 Human Subject Research Experiment Design and Procedures

Each subject attempted a manual mode, a shared control mode without the fuzzy logic interpreter, and a shared control mode with the fuzzy logic interpreter. The manual mode was the base from which the other modes were compared in order to determine their unique challenges and difficulty.

Human Subject Research Protocol Procedure:

1. Pre-Training Session
2. Training Sessions
3. Practice Sessions
4. Obstacle Course(s)
5. Questionnaire
6. End of Study

Refer to the timeline in Figure 12 for the duration of the study.

4.2.1 Pre-Training Sessions

During the Pre-Training Session, the Emotiv EEG headset was fitted on the subject. This was to determine if the headset would fit them and to see if a connection could be made. If they were able to connect, then they would be considered for the study. The most common failures were a result of the size and shape of the subject’s head and the density of the subject's hair. These factors could prevent the headset from sitting on the head properly and reduce connectivity to the electrodes. Pre-training determines if the fit would not work well on a, subject before they get heavily involved in the study. This process is relatively brief, about 30 minutes, compared to the rest of the study which can take months to complete.

4.2.2 Training Sessions

Once it is confirmed that the subject can use the headset, they can start doing the training sessions. During the training session, training samples are collected. There are three different training samples taken for cognitive, facial, and speech detection. These training samples are used by the software to recognize the cognitive, facial, or commands. Cognitive training collects 8 second samples of EEG recordings. The subject must think of the mental command during this 8 second sample. Facial training also collects an 8 second sample but this time the subject will physically preform a facial expression to. Facial training does not always require samples as the universal signature tends to work well for most individuals. Cognitive and facial training require a neutral action to be trained. This neutral action is really a neutral state where the user is relaxed and not attempting to stimulate their mind or make a facial expression. For facial training of the neutral action, the subjects is asked to relax and not blink. Lastly, speech training requires subjects to read a prompt activated through the built-in Microsoft Speech Recognition software. Unique speech profiles will be created which will allow the software to better detect their verbal commands. After the commands are created, the subjects have a chance to get familiar with the new movement style of the wheelchair since it is a significantly different experience when the wheelchair is in manual mode than autonomous mode.

4.2.3 Practice Session

When the users are completely confident of their commands they do a practice session. This is where they get to use the commands with the autonomous mode on. During the practice session, commands are requested to be performed. If the subjects can do the commands successfully, they move onto the obstacle course. If they are not able to do certain commands, additional training sessions are conducted to collect more samples to increase the reliability of the command (or likeness of the command to be recognized by the software).

4.2.4 Obstacle Courses

Various courses were designed for the obstacle sessions. There are 3 obstacle courses proposed in the human subject protocol. All the obstacle courses were setup in a classroom with barrels, tables, and markings per applicable course. These were proposed but not necessarily completed by all subjects due to various situations such as time commitment and scheduling.

The first obstacle course was designed to provide the subjects with more than one path to take, in order to give them choices so they do not rely solely on the autonomous features. Refer to Figure 13 for the layout of obstacle course 1 and an example of a path that the wheelchair may take for this setup. The barrels and tables used for this course can be seen in Figure 14 which is an image of the actual obstacle course.

The second obstacle course has waypoints, locations or goals, to travel to. This is to simulate going to and from locations in a daily life setting and to add a more complex situation for the subjects to navigate. Refer to Figure 15 for the layout of obstacle course 2.

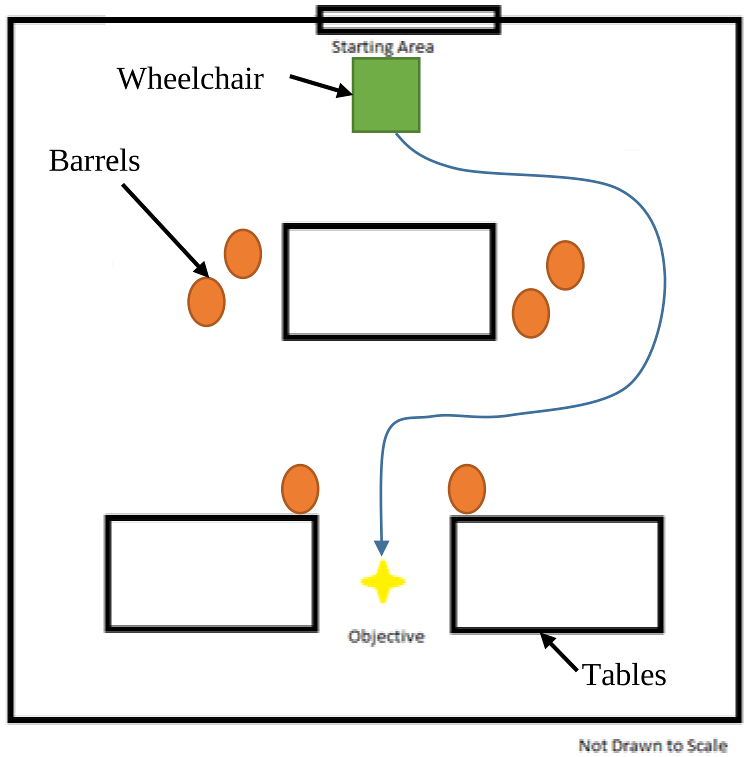


Figure 13: Obstacle Course 1 Layout

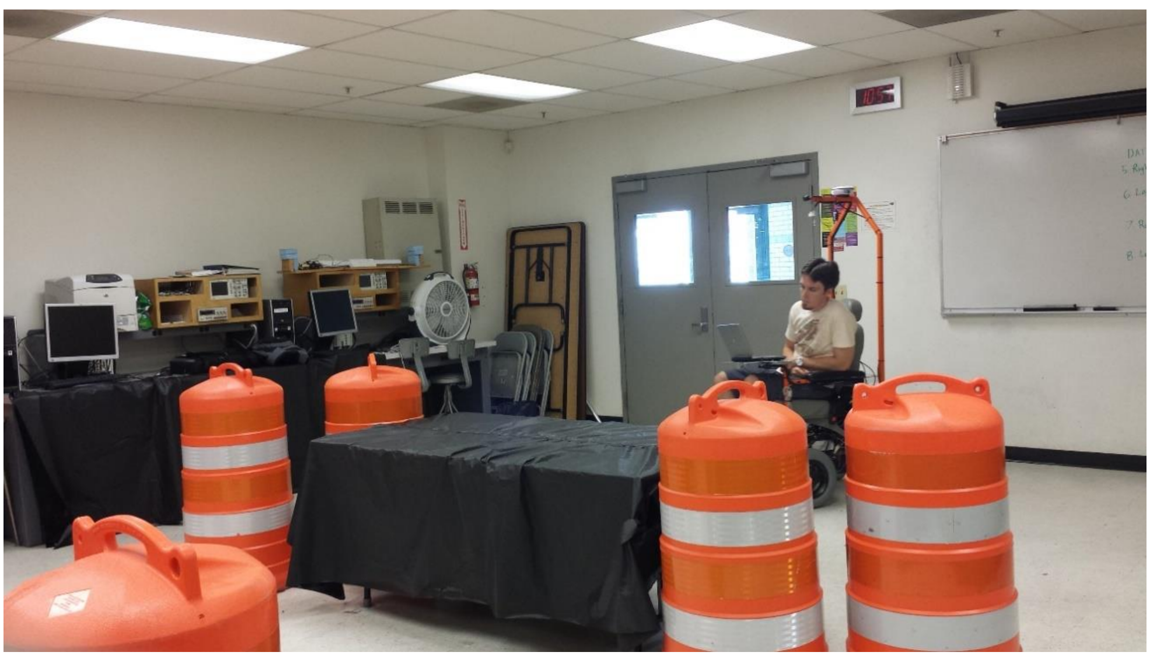


Figure 14: Image of Classroom Setup

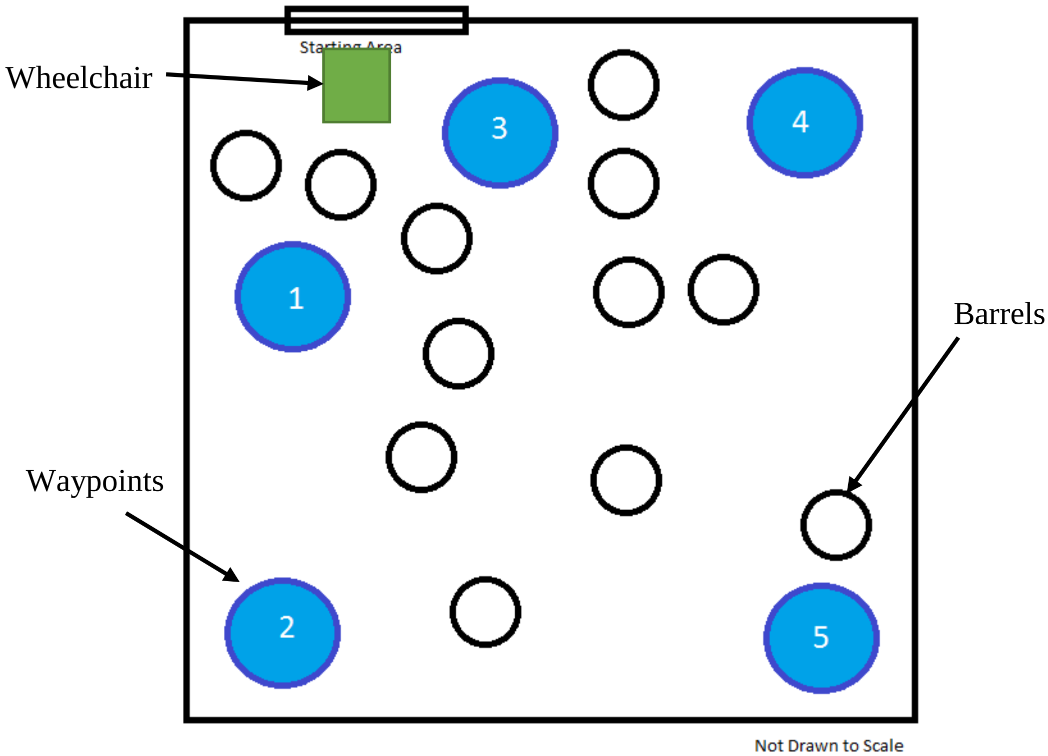


Figure 15: Obstacle Course 2 Layout

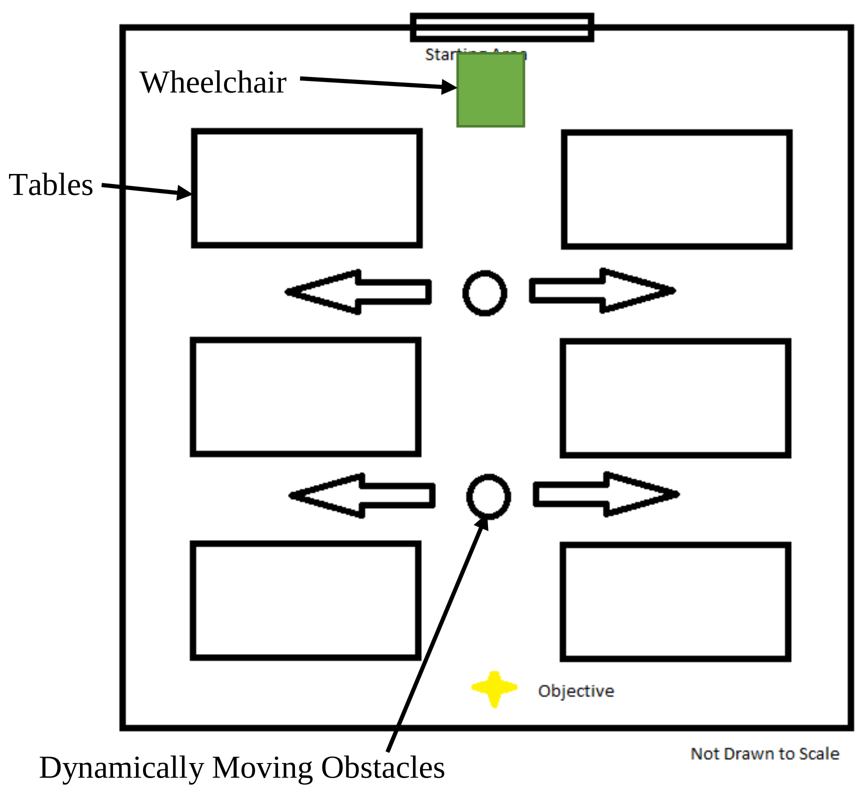


Figure 16: Obstacle Course 3 Layout

The third obstacle course has only one path but moving obstacles to simulate the dynamically changing atmosphere of a real life situation; travelling through a hallway with peers walking by or crossing paths with the user, refer to Figure 16.

These courses were meant to compare the different shared control modes with the autonomous features and the multimodal commands, as well as to see how well the wheelchair and the subjects perform when navigating through different courses. During the obstacle courses, observations were made such as erroneous operations by the user or the wheelchair, completion of course, and duration of completion, if applicable. Data was collected from motor encoders, predicted paths taken, and other vehicle parameters to determine distances taken. The results will be discussed in more detail in section 5.0.

5.0 RESULTS

The following section will discuss the results of the study are: 1. Evaluation of Commands Execution, 2. Evaluation of Intelligent Wheelchair Performance. The results are from training sessions, practice sessions, and obstacle course 1 sessions. Due to lack of completion by the subjects, obstacle courses 2 and 3 are not discussed in these results. These items are outlined in the following subsections. Refer to the APPENDIX C for more details on the data collection such as standard deviations, maximum values, and minimum values.

5.1 Evaluation of Training Success and Command Execution

1. Total Training Session Time: The total time for all the training sessions.
2. Sample Ratio: The total samples used for command recognition over the total samples taken per command type.
3. Frequency of Commands Used: The average amount of commands per type and control mode.
4. Frustration Score: The average value of the emotional state of frustration detected by the Emotiv EEG headset collected during each run.

The total training session time per subject is summarized in Figure 17. The training sessions included activities such as taking samples, command executions, and practice of commands (speech, facial, and cognitive). The actual training sessions may take longer than projected as it does not account for equipment set up and interruptions. These training sessions were on a weekly basis and can vary between 1-2 hours per session for several months.

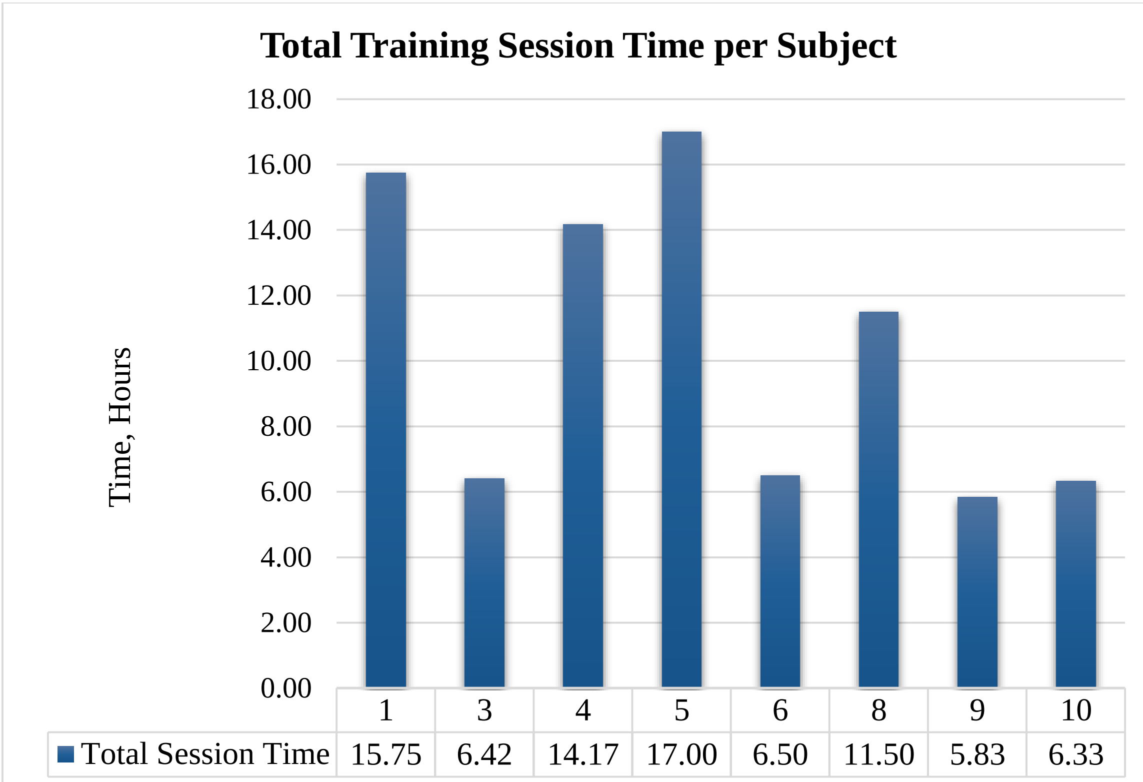


Figure 17: Total Training Session Time per Subject

Cognitive command recognition training contributed to the bulk of the time for training sessions. Subject 1 and 4 can execute more than 1 cognitive commands. Subject 5 and 8 were having inconsistencies executing their cognitive commands but made extra effort to use a single cognitive command. This could explain why their training sessions were longer than the rest. Subject 3 did not use cognitive commands but attempted cognitive training. Subject 6, 9, and 10 trained only one cognitive command. One cognitive command or less may contribute to lower training session times. Majority of the impact on the total training session time was due to cognitive command training.

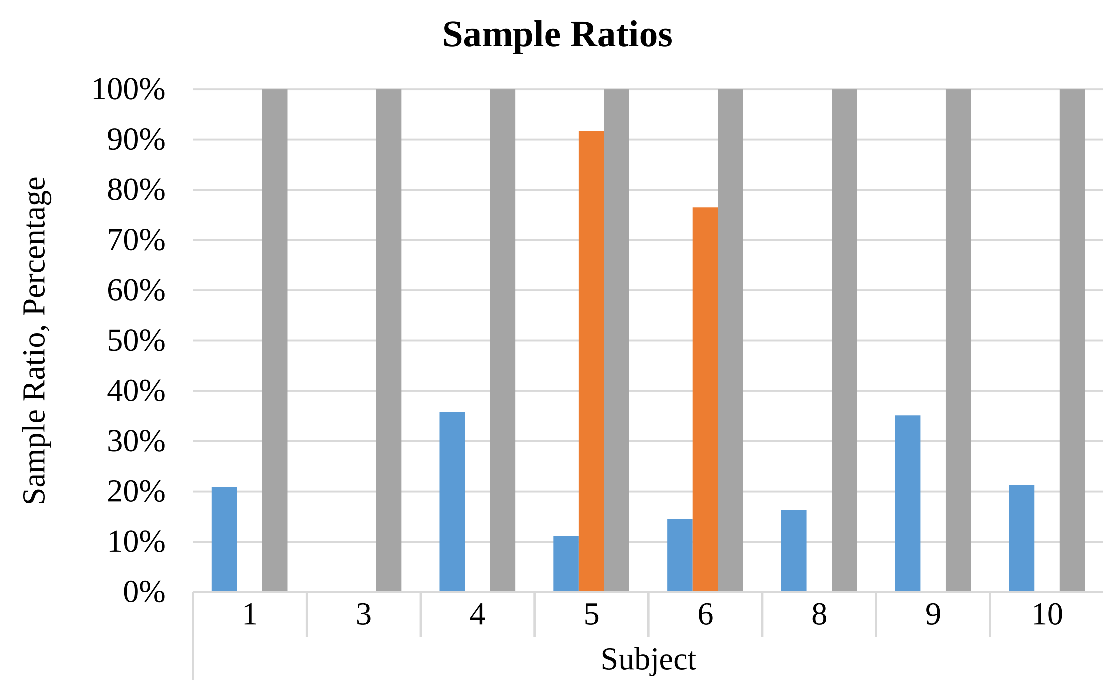
Speech command training required one training set and is simple to do. Subject 6 was the only subject that required multiple speech command samples. Other than that subject, only one sample was acquired from all other subjects. Speech training is relatively quick and may only take about 10-15 minutes to complete which does not impact the training session significantly.

Facial command training does not normally require samples taken as it works for most individuals. Subjects 3, 5, and 6 went through facial command training. Despite facial command training, Subject 3 could not manage facial commands. Subject 1 did some facial command training but did not use the samples instead they used the universal signature that required no training. No samples were acquired from all other subjects. These subjects used the universal signature.

The results show varying times per subject. This was a result of the different efforts needed to collect the varying command recognition samples. Each subject had individual or common challenges that may have contributed to longer training session times.

The sample ratio represents the percentage of the amount of samples used for the training set for command recognition over the total samples attempted for command recognition. The percentages are summarized in Figure 18. For reference, the blank spaces in the facial sample ratios refers to those subjects using the universal signature which required no facial command training.

The sample ratios for cognitive command training varies per subject but overall is low compared to facial and speech command training. During the cognitive command training process, a lot of samples were collected but not every sample was accepted by the subject or the subject was unable to manage the cognitive command with the collected sample. In the case the subject was unable to manage the command, more samples were collected to replace the training set. Due to sample rejection, significant amount of samples were collected but only a few were used to create a cognitive command which resulted in low sample ratios.



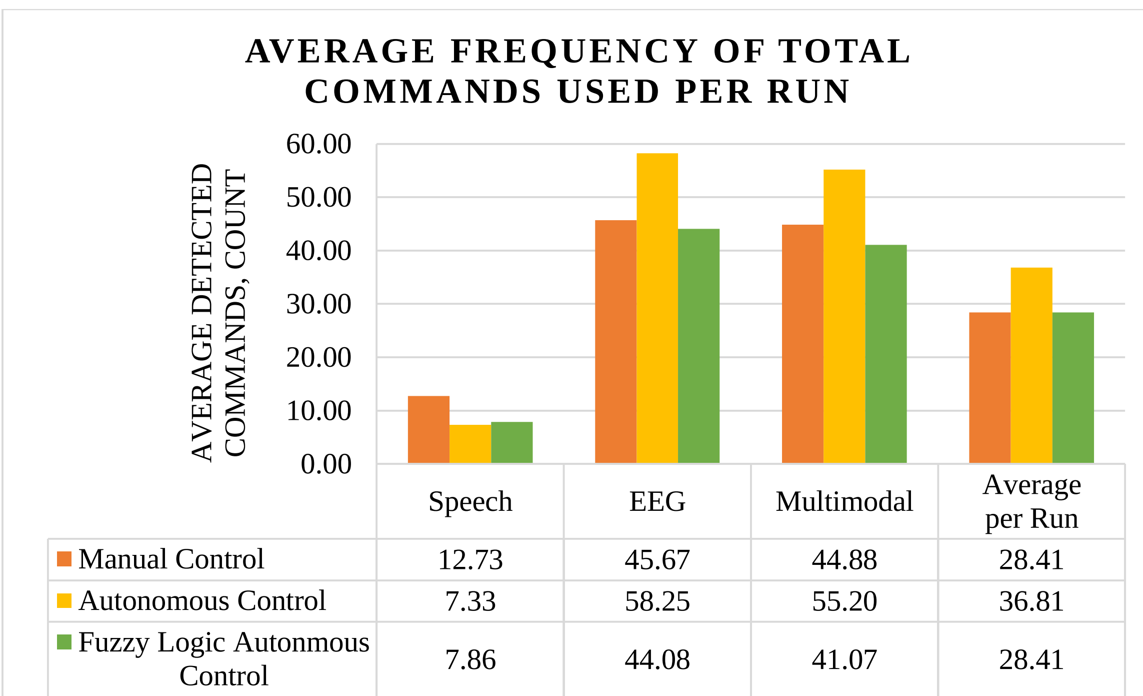
	1	3	4	5	6	8	9	10
Cognitive	21%	0%	36%	11%	15%	16%	35%	21%
Facial		0%		92%	76%			
Speech	100%	100%	100%	100%	100%	100%	100%	100%

Figure 18: Sample Ratios per Command Type

The sample ratio for facial command training was almost unnecessary as the device was able to detect most of the subjects' facial expressions. Almost all of the subjects used the universal signature without the need to do facial command training. Subject 5 and 6 required facial command training. Recall that Subject 3 went through facial training, but was unable to manage the commands. This is reflected by the 0% sample ratio. There are 3 out of 8 subjects that underwent the full facial command training process where 1 out of those 3 subjects failed to use facial commands completely.

The sample ratios for speech command training are all 100% because all samples collected were used. For most subjects, only one training set was collected for the speech command recognition. In ideal conditions, the speech commands were registered with no problem.

Frequency of commands used is the average of the amount of commands used during the obstacle course sessions. The results are summarized in Figure 19-Figure 22 representing all commands used, and the different control modes (manual, autonomous, fuzzy logic autonomous). In the content of the figures, “Speech” refers to obstacles sessions where only speech commands were used. “EEG” refers to obstacles sessions where only cognitive and facial commands were used. “Multimodal” refers to obstacle sessions where speech, cognitive, and facial commands were used.



	Speech	EEG	Multimodal	Average per Run
Manual Control	12.73	45.67	44.88	28.41
Autonomous Control	7.33	58.25	55.20	36.81
Fuzzy Logic Autonmous Control	7.86	44.08	41.07	28.41

Figure 19: Frequency of Commands Used per Control Type and Obstacle Course 1 Run Type

Based on the total commands used, refer to Figure 19, speech commands were used less often than cognitive and facial commands combined in general. In the sessions where speech was the only mode of command, there were less speech commands used when shared control was used compared to manual control. To see the cognitive commands and the facial commands separately, the different control modes are separated and the different averages of the commands used in these modes are identified in Figure 20-Figure 22.

Based on the different control modes in Figure 19, the average frequency of commands in the fuzzy logic autonomous mode is less than the manual control. The autonomous mode without fuzzy logic is the main wheelchair navigation system. The fuzzy logic autonomous control is an improvement to the main navigation system as well as having less commands executed during this mode than manual control. The values of the frequency of cognitive and facial commands for the fuzzy logic system is still close to manual control values. This was due to erroneous operation in the fuzzy logic autonomous mode (as well as in the autonomous mode without fuzzy logic) where the wheelchair travelled undesirably such as multiple turns around the objective or improper calibration of the LRF position on the chair rendering obstacle avoidance less accurate. These erroneous operations also lead to more collisions, refer to Section 5.2.

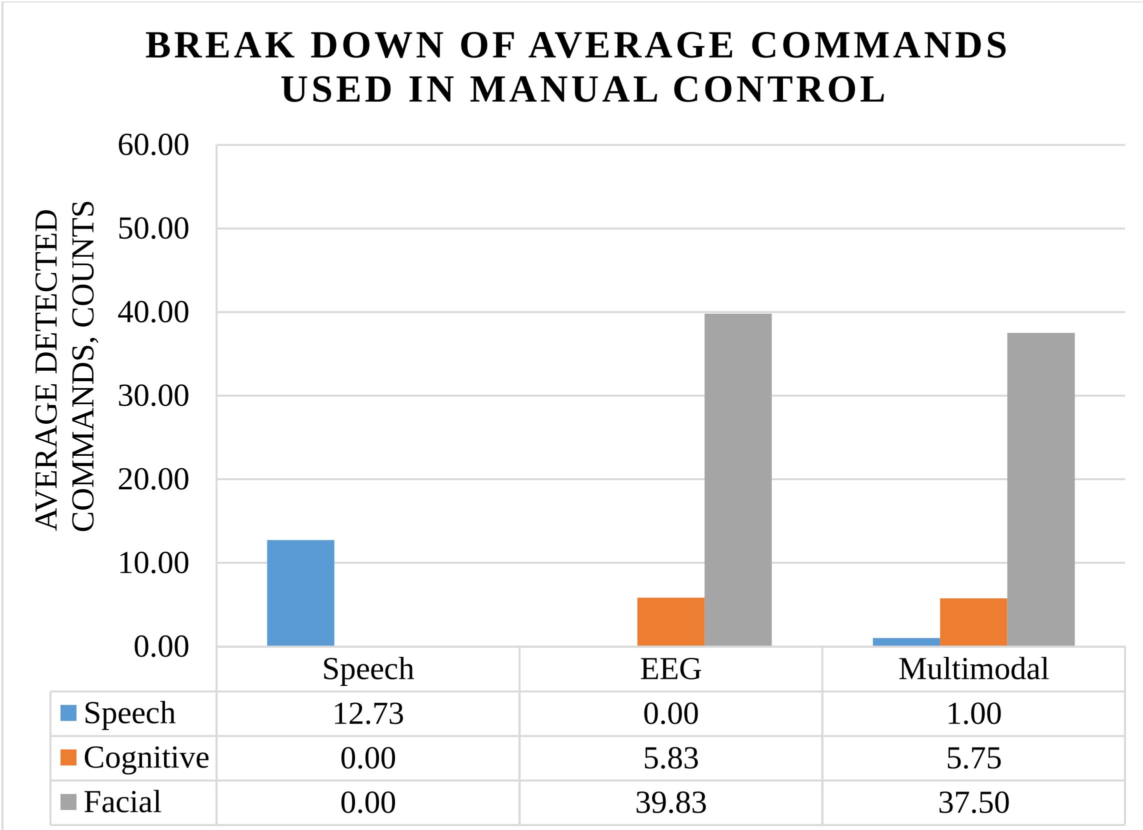


Figure 20: Break Down of Average Commands used in Manual Control

In manual control, refer to Figure 20, facial commands were used the most. Cognitive commands were used less often than speech commands when compared between speech only runs and runs with combined cognitive and facial commands. When subjects were allowed to decide to pick any combination of commands, speech commands were used the least and the facial commands were used the most. Cognitive commands, in this case, were used more than speech but relatively low in comparison to facial commands. It appears from the usage of commands in the manual control that facial commands are most preferred and speech the least preferred. This preference is repeated in autonomous control and fuzzy logic autonomous control, refer to Figure 21 and Figure 22 respectively.

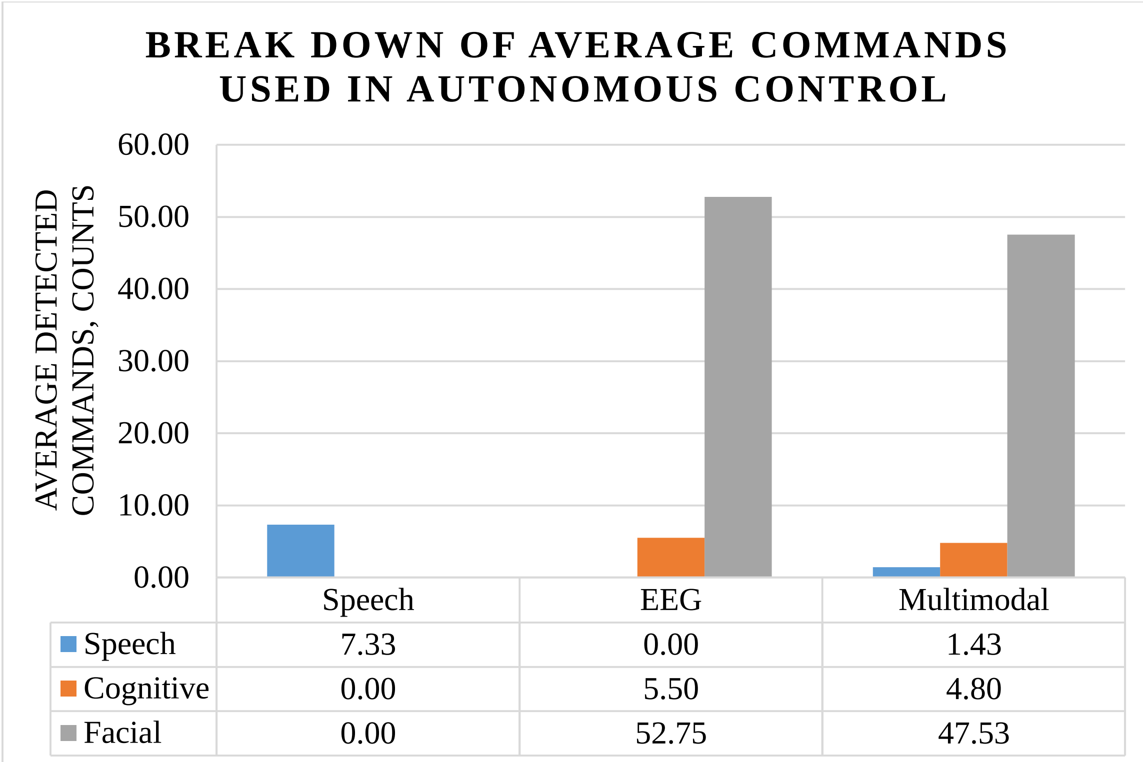


Figure 21: Break Down of Average Commands Used in Autonomous Control

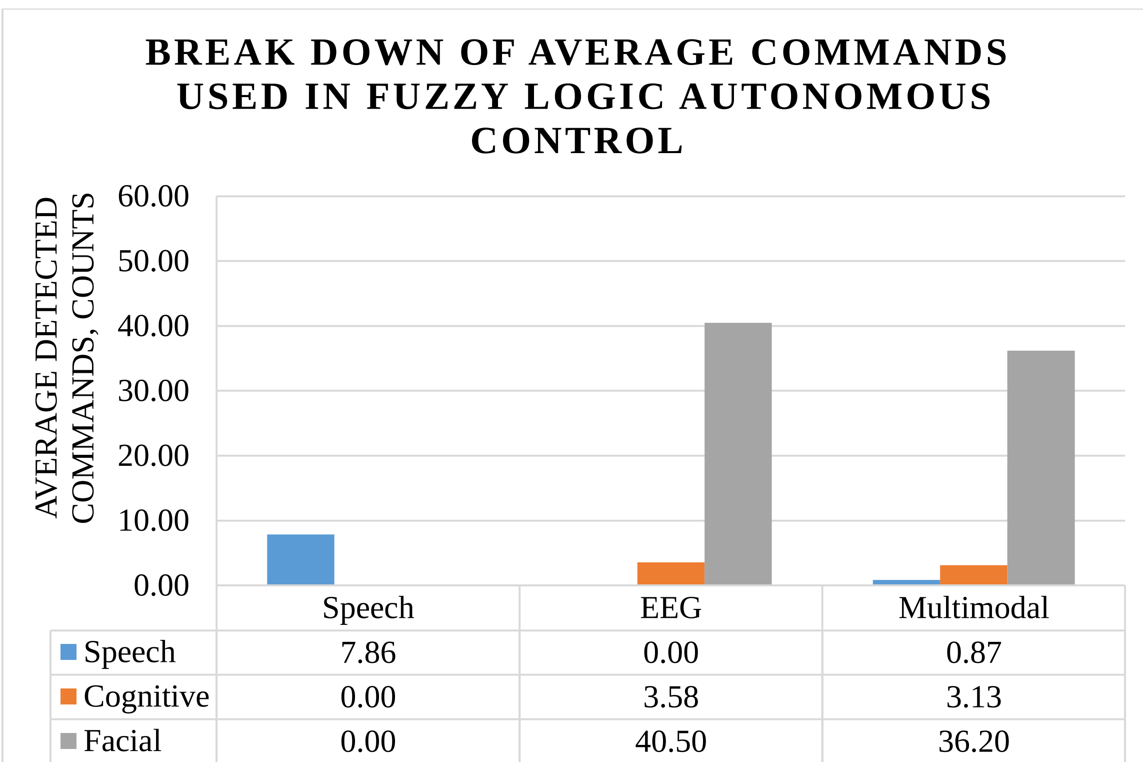


Figure 22: Break Down of Average Commands Used in Fuzzy Logic Autonomous Control

The frustration score is the average value of the emotional state of frustration detected by the Emotiv EEG headset collected during an entire run. This value was collected to evaluate if frustration levels can be lowered using shared control. The average frustration scores are summarized in Table 4. Unfortunately, due to technical difficulties the frustration scores were not acquired during the speech only sessions. Based on the average frustration scores, shared control had lower values than manual control. Fuzzy logic autonomous control had the lowest overall average.

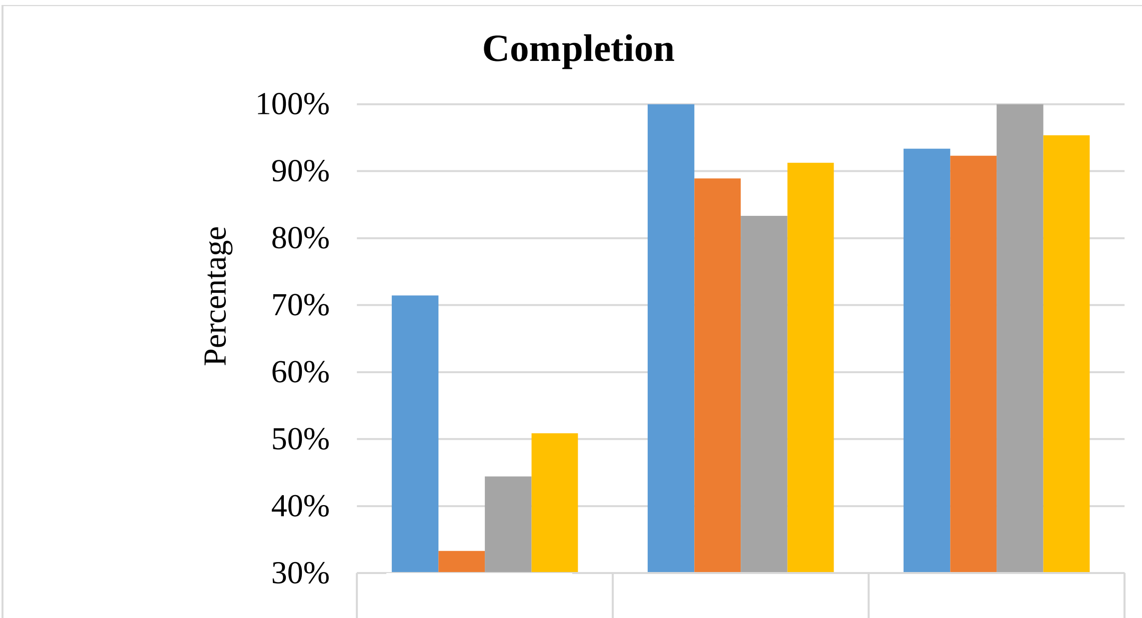
Table 4: Frustration Scores

Control Mode	**Command Type**	**Frustration Score Average**
Manual Control	Speech	N/A
	EEG	0.72
	All	0.62
	Total	0.66
Autonomous Control	Speech	N/A
	EEG	0.60
	All	0.63
	Total	0.62
Fuzzy Logic Autonomous Control	Speech	N/A
	EEG	0.63
	All	0.56
	Total	0.59

5.2 Evaluation of Intelligent Wheelchair Navigation Performance

1. Objective Completion: The percentage of completed objectives over the total amount of runs attempted per category
2. Time: The average time taken to complete the objective of all runs per category in seconds
3. Number of Collisions: The average number of collisions per category
4. Distance Travelled per Wheel: The average distance travel per wheel based on motor encoder counter converted to meters per category

The results of the runs recorded where the objectives were completed are summarized as the percentage of completed objectives over the total amount of runs attempted per category in Figure 23. There is a significant improvement of completed objectives using shared control compared to manual control, there is an increase of 40% or greater of the completed objectives in shared control than in manual control. Fuzzy logic autonomous control has a 4% increase of total runs completion compared to autonomous control without fuzzy logic.

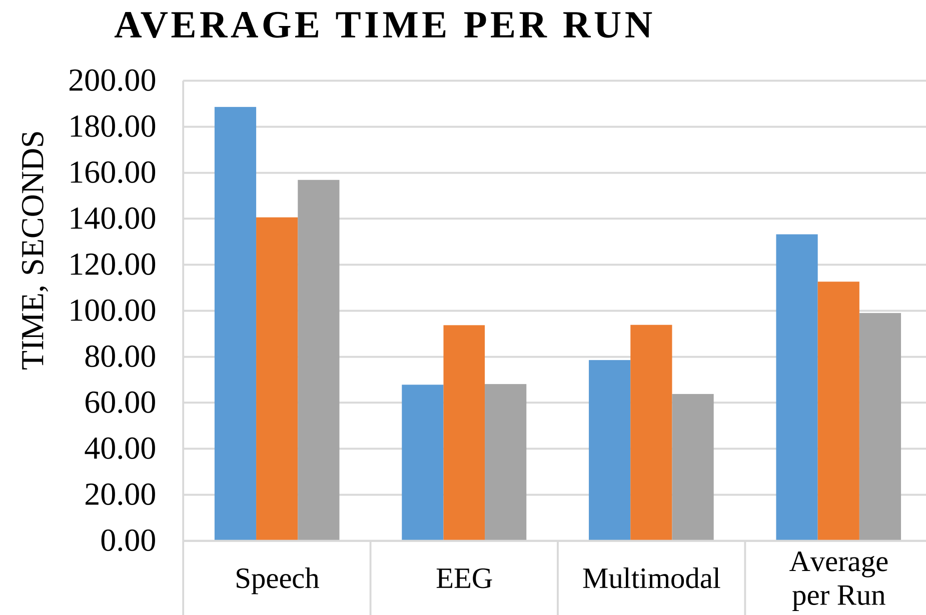


	Manual Control	Autonomous Control	Fuzzy Logic Autonomous Control
Speech	71%	100%	93%
EEG	33%	89%	92%
Multimodal	44%	83%	100%
All Runs per Control Mode	51%	91%	95%

Figure 23: Objective Completion Percentages

The time was recorded for each run and the average time taken to complete the objective of all runs per category in seconds is summarized in Figure 24. Runs that used speech commands only, have the longest run times due to the wheelchair stopping during a collection of a speech command. Autonomous control without fuzzy logic surprisingly has the highest average time when using a combination of cognitive and facial ("EEG" column) commands and a combination of commands picked by the subjects ("Multimodal" column). Despite having longer than expected results, averaging all the runs for autonomous control without fuzzy logic performs better than manual control. Based on the subjects' comments, the fuzzy logic felt more responsive to their commands. This could be why the fuzzy logic autonomous mode had shorter run times compared to the other control modes as well as similar frequency of commands used during manual control mode. Manual control has the highest average times of all the runs, autonomous control has the second highest average time, and lastly, fuzzy logic autonomous control has the lowest overall time.

To evaluate the performance of the wheelchair navigation, the number of collisions was recorded. To summarize the number of collisions recorded per run the average was calculated and represented in Table 5. Despite having obstacle avoidance algorithms for motion control, there are more collisions occurring in both autonomous modes. The fuzzy logic autonomous mode has a smaller average for collisions compared to the autonomous mode without fuzzy logic. Manual control has the lowest average of collisions. Therefore, the autonomous modes are not reducing the amount of collisions and did not perform as well as manual control.



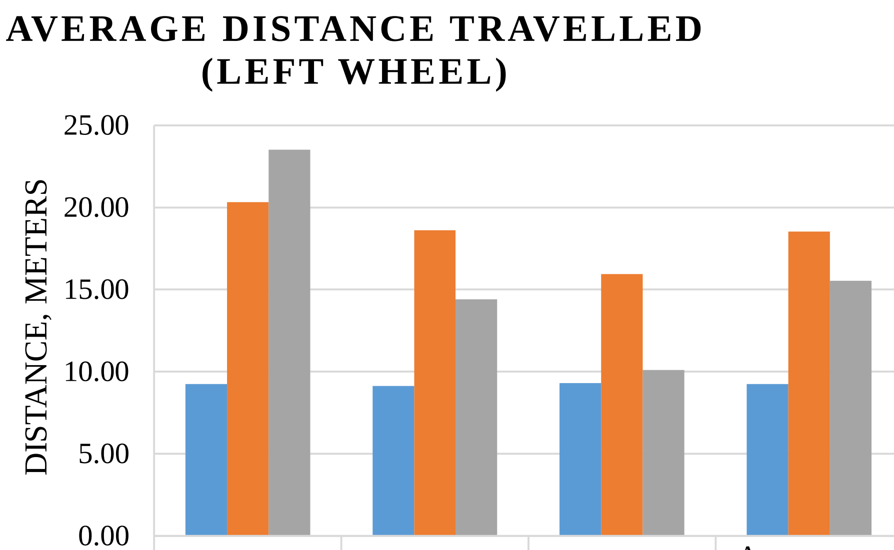
	Speech	EEG	Multimodal	Average per Run
Manual Control	188.58	67.84	78.61	133.26
Autonomous Control	140.54	93.71	93.90	112.68
Fuzzy Logic Autonmous Control	156.84	68.12	63.78	98.93

Figure 24: Average Time (in seconds) to Complete Objective per Run

Table 5: Number Collisions per Mode and Command Type

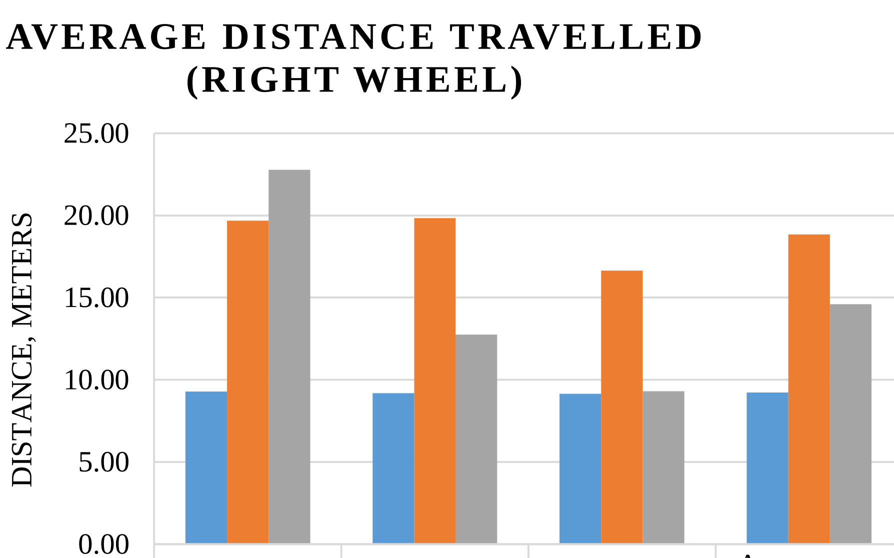
Control Mode	Command Type	Average Collisions
Manual Control	Speech	0.20
	EEG	0.17
	All	0.13
	Total	0.17
Autonomous Control	Speech	0.95
	EEG	0.63
	All	0.53
	Total	0.73
Fuzzy Logic Autonomous Control	Speech	1.07
	EEG	0.33
	All	0.20
	Total	0.51

To evaluate if the wheelchair navigation is taking an optimal path (shortest distance travelled), the distance the wheelchair travelled was recorded. Unfortunately, due to errors in the logs actual recorded paths were not taken so instead motor encoder data was used to calculate the distance travelled per wheel. The distance the wheelchair travelled was evaluated per wheel in meters. Motor encoder counts per wheel was collected converted to distance travelled per wheel, the summary of the average distance travelled is represented in Figure 25 and Figure 26. In manual control, the distances travelled are very consistent between the different command types and are the shortest distances travelled, approximately 9.1-9.3 meters. The shorter distances may be due to the stop and go nature of manual control which reduced the tendency to overshoot the objective area as well as the subjects being observant of the surrounding obstacles. The fuzzy logic autonomous control had the largest variation in distance travelled between the different command types and had a shorter distance travelled based on all the runs collected compared to the autonomous mode without fuzzy logic. Fuzzy logic autonomous control has the largest distances travelled while using speech commands only. It appears that the fuzzy logic autonomous control may be struggling with speech commands as the mechanism for interpreting the command is different than cognitive and facial commands.



	Speech	EEG	Multimodal	Average per Run
Manual Control	9.25	9.14	9.31	9.24
Autonomous Control	20.32	18.60	15.95	18.53
Fuzzy Logic Autonmous Control	23.52	14.41	10.11	15.53

Figure 25: Average Distance Travelled by Left Wheel



	Speech	EEG	Multimodal	Average per Run
Manual Control	9.29	9.20	9.15	9.23
Autonomous Control	19.68	19.83	16.65	18.85
Fuzzy Logic Autonmous Control	22.78	12.76	9.30	14.60

Figure 26: Average Distance Travelled by Right Wheel

6.0 CONCLUSIONS

In conclusion, the shared control method utilizing a fuzzy logic interpreter to distinguish user heading in combination with hands free commands created by the user for an autonomous hybrid BCI wheelchair is feasible. The fuzzy logic autonomous shared control has a high success rate for completion of the objective and has the fastest average run times. The distances travelled in this mode and the lack reduction of the number collisions compared to manual control can be due to the autonomous path planning and motion control, as the results for autonomous control without fuzzy logic performed in a similar fashion. It is also interesting to note that the fuzzy logic autonomous mode has the lowest frustration score. Based on observations, the subjects like the responsiveness to their commands in this mode. The fuzzy logic interpreter is a viable addition to this intelligent powered wheelchair.

In manual control mode, shorter distances were achieved and had the lower average of collisions per run. In this mode, there is no assistance from the decision making part of the algorithms. Based on observations during the runs for this mode, subjects actively are making judgements to prevent collisions prior to moving. Making these active assessment requires some time to make reasonable judgements to deliver a command which can be seen in the longer run times for manual control. The clearance between the obstacles and the wheelchair were much smaller than what the tolerances were allowed during autonomous mode of the wheelchair. It appears that despite having path planning, algorithms for decision making, and a larger safety zone, the wheelchair autonomous control modes with or without fuzzy logic clearly need a better sense of what users' desire as safe. Despite this, more objectives were completed during the autonomous modes compared to manual control. The users play an important part of the decision making process and their decisions should be rated higher than the decisions from the machine. The machine's role should be to assist the user since the successful rate of completely the objective is higher rather than dominating the decision making process from the user.

The fuzzy logic autonomous shared control performs as well or better than the autonomous shared control without fuzzy logic, refer to Table 6: Summary of Intelligent Wheelchair Navigation Performance Values Table 6. The fuzzy logic autonomous shared control also out performed manual control in objective completion and run times. Future improvement to the fuzzy logic interpreter, the autonomous algorithms, and sensor range may improve the reduction of collisions, reduce distance travelled, and improve command responsiveness, refer to section 6.1.

Table 6: Summary of Intelligent Wheelchair Navigation Performance Values

Intelligent Wheelchair Navigation Performance Values					For Reference
Mode	Objective Completion	Completion Time	Average Collision Encountered	Distances Travelled	Frustration Scores
Manual Control	Low	Slowest	Low	Shortest	0.66
Autonomous Control	High	Faster	Medium	Furthest	0.62
Fuzzy Logic Autonomous Control	High	Fastest	Medium	In-between Manual and Autonomous Control	0.59

Subjects faced a lot of challenges using the BCI wheelchair. One of the most obvious challenges for the individual was learning how to activate their cognitive commands. The relationship between the thought and the activation of the command is more complicated than they expected. This is seen through the results where there are longer training sessions times with subjects attempting multiple cognitive commands, low sample ratios (meaning more samples taken but low success of useful training samples), and low frequency of usage. From observations, the low frequency was due to the lack of confidence the subjects had utilizing this type of command. There is a learning curve per each individual. To learn how to use the cognitive functions of a BCI wheelchair is like learning how to use a new muscle. Cognitive training is an important part of using the commands with confidence and it is the most challenging.

Facial commands were the most used and required no or little additional training. The sample ratio for facial commands is high for samples taken for training. Most of the samples were useful and aided in facial command detection. The frequency of use of facial commands was extremely high. It was easy to use and manage. A disadvantage to this is instead of reducing the commands the user needs to use, it increases it, making the users more actively control the motion of the wheelchair instead of letting the autonomous controls do the work. Facial commands are preferred method for the subjects giving them more control over the wheelchair movement.

Speech commands are fairly easy to train and use except when it does not detect correctly. The training session was short and in ideal situations has not required additional training. Due to the length of time required to use a speech command, the frequency of the commands was low. Another possible reason for the infrequent use of this command is due to not detecting the verbal input correctly. This could be due to hardware limitations and external noise which can be easily fixed as better hardware is available off the shelf.

The obstacles course is a controlled setting and may not reflect the realistic challenges these commands will face during everyday usage. The results do not reflect other issues. For example, speech commands may not always detect your inputs or detect them correctly forcing repetitive vocal inputs which can be disruptive. When you are in a meeting or a classroom and the user wants to adjust the position of their wheelchair, they need to speak out loud and by doing that can be distracting to others. In addition, the particular way these commands are executed for this study is lengthy. If the user wants to get somewhere in a hurry, they may not want to use speech commands. So maybe using cognitive or facial commands are better since you do not have to speak out loud. Well these command types have other issues as well. Facial commands are used most frequently but if the user wanted to talk to someone, that movement of the face can also move the wheelchair when the user may not want it to move at all. To create a facial command depending on the facial expression used it may look silly or may create embarrassing facial gestures that imply suggestive body language creating undesired attention to the user. Cognitive commands may be the best choice to have discrete commands without being disruptive but it requires a lot of concentration and focus so in loud and distracting environments it may difficult to execute. Each type of command has its unique problems in a real setting.

Based on the results and issues discussed in the paragraph above, the command types make be used in a different applications so that they are more effective, refer to section 6.1 for future applications of these commands for the BCI wheelchair. In summary, refer to Table 7, for recommended applications for the different command types. For speech commands, the commands can be shorten to activate or disable features such as a hotkey that turns on and off the autonomous modes that assist the user. Or have command phrases or statements to communicate different actions. For example, telling the machine to drive you to the local store similarly like how a person would talk to their standalone personal GPS device or smartphone to assist with driving directions. This would reduce the amount of time to execute the speech commands as well as being more direct with the machine. Due to the challenges of cognitive commands, simplifying how they are used would make them more effective as well as restricting to one command. For example, use a cognitive command to changing the speed of the wheelchair by looking at the duration of a cognitive commend. The longer an individual concentrates on their cognitive command the faster the wheelchair will move or the concentrating for smaller amount of time will slow the vehicle down. Another example would be to use other features of the brain signals to use as inputs for the fuzzy logic interpreter to improve the effectiveness of a command such as concentration, focus, medication, and/or excitement but not limited to these signals. Lastly, facial commands are really a detection of muscle movements so instead of restricting to only facial expressions, other muscle actuations could be detected. This would alleviate the face to do other things such as talking to peers.

Table 7: Recommended Applications for Command Types

Command Type	**Application**
Speech	Use phrases to communicate to different features, i.e. Outdoor Navigation, or a hot key enabling features
Cognitive	Use emotional states such as frustration, excitement, and/or meditation for additional inputs i.e. Speed Control or inputs to assist the Fuzzy Logic
Facial	Consider other muscle actuations on the body

For a summary of the evaluation of training success and command execution, refer to Table 8. Facial commands are used the most than all other commands. Speech commands appear to have a good execution rate for all modes as in they have a low frequency of use. During the different control modes, speech commands have high successful rates of completion. It can be concluded that speech and facial commands are both preferred methods of sending commands to the machine. Cognitive commands due to the challenges of executing and training this command type may be preferred the least.

Table 8: Summary of Evaluation of Training Success and Command Execution

Evaluation of Training Success and Command Execution				User Preference based on this evaluation
Command Type	Training Session Time	Sample Ratio	Frequency of Commands	
Speech	Short	High	Low	Preferable
Cognitive	Very Long	Low	Lowest	Least Preferred
Facial	None or some training required	High	High	Most Preferred

6.1 Future Work

In retrospect, the fuzzy system that interprets the intended heading prior to correcting it, would need additional fuzzy sets to better determine the intention of the user. The fuzzy system that interprets intent can be improved by using levels of meditation and frustration to assist. For example, if the user is in a high level of meditation and a low level of frustration then the intent is more than likely true. Or if the user is in a low level of meditation and a high level of frustration then the intent is less likely to be true or more likely to be false.

The fuzzy system for correcting the heading by using the concept of obstacle avoidance was simplified to use only 3 points of interest. This was due to limitations of the software. It is desired to use a complex fuzzy set instead of the traditional membership functions. A complex fuzzy set refers to a fuzzy set that is dynamically changing based on the full range of the distances of obstacles from the available sensors. Conceptually, this should be possible but the toolkits used for developing the software could not interpret a complex fuzzy set like that. During the next software development phase, a technique should be considered to take the raw LRF data and create a fuzzy set from it for objects that are near or far. The fuzzy set would change dynamically as the environment changes. This would be used instead of the current fuzzy sets which determined what objects were near or far from the Intended Heading, and a little bit left and right of it. In addition, the wheelchair algorithm would need to either change to accept the range of the LRF to go beyond the range of 180° to 270°, or temporarily save data on the location of nearby obstacles to reduce collisions.

One of the difficulties the subjects faced was the drifting and whipping motion of the wheelchair. The path planning and motion control of the powered wheelchair was originally used for an unmanned autonomous vehicle. The wheelchair navigation was not optimized for rider comfort. The algorithms for path planning and motion control should be revamped for user comfort. I recommend two possible solutions to this problem. One option for preventing the whipping motion is to change the path planning algorithm from a radial path planning concept to one that reduces the rotational motion required to get to a destination. In addition, there could be a simulated brake or install a physical brake system on the wheelchair platform. The second option, is to develop a fuzzy logic controller with a knowledge base created using the experience from the human study. This would be then used in an adaptive fuzzy control to optimize path planning which will smooth out motion control.

The wheelchair navigation for autonomous mode is continuously moving and may not be desirable in all situations. There are no options to stop or do nothing in a situation where the user commands and the allowable paths that are deemed safe are conflicting. Also in some situations users may actually want to approach obstacles. For example, a user may want to read something posted on the wall or approach a friend in the hallway. The current system will avoid them such as turning away from them or travel past them. Subjects made comments that they preferred to move backwards instead of continuously moving forward if they missed their objective during an obstacle course session. The ability to move backwards only occurs during a dead end situation in the current system. This back up feature needs a user override so that the users have more control over the desired paths. More conditional cases and back up options need to be added to the system to make better predictions of what is desirable for the wheelchair navigation.

The type of commands for the BCI wheelchair may remain the same but used for different applications as well as changing the mechanism of which they are being activated. Speech commands could be shortened and streamlined for quick commands to reduce the length of execution. They may be used only for outdoor navigation to tell the wheelchair something along the lines of saying, “Drive me to the nearest grocery store.” Using keywords such as “drive” or “take me” to let the machine know the user wants to go somewhere. Using keywords such as “nearest” or “fastest” to determine the route that is taken. Other descriptive keywords could determine the particular location that can be located by using GPS. Cognitive commands can be used for toggling like turning something on and off or throttling like changing the speed of the wheelchair. Facial commands can continued to be used but maybe using a more discrete way. For example, a user may want to control their wheelchair while having a conversation with a peer but to constantly smirking or winking may be disruptive to their conversation. These are some ideas for improvements of the different applications these commands can be used for.

For future human studies using the same procedures, the clearance between the obstacles and the wheelchair should be recorded. This can be used to evaluate the wheelchair navigation performance. Additionally, a different study could be made to see how close subjects actually want to get to obstacles to alert the safety tolerances.

Ultimately, in the future, it would be desirable to work with target audience who would benefit the most from the intelligent wheelchair.

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APPENDIX A

The following are generated from LabVIEW using the Fuzzy System Designer tool of the fuzzy logic systems implemented for the human study.

Fuzzy System for Intended Heading

The filename for this system is Fuzzy v4.fs.

Input variables

Table 9: Input Variables in Fuzzy Logic Design for Intended Heading

Name	**Range**	**Number of membership functions**
Intent	0 to 4	3
Concentration	0 to 100	3

Output variables

Table 10: Output Variable used in the Fuzzy Logic Design for Intended Heading

Name	**Range**	**Number of membership functions**
Intended Headiing	-90 to 90	7

Defuzzification method: Center of Maximum

Input membership functions:

Intent

Table 11: "Intent" Membership Function Shape and Points used in the Fuzzy Logic Design for Intended Heading

Membership function	**Shape**	**Points**
Left	Singleton	2
Forward	Singleton	1
Right	Singleton	3

Concentration

Table 12:"Concentration" Membership Function Shape and Points used in the Fuzzy Logic Design for Intended Heading

Membership function	Shape	Points
Very Sure	Trapezoid	50 ; 75 ; 100 ; 100
Sure	Triangle	25 ; 50 ; 75
Not So Sure	Trapezoid	0 ; 0 ; 25 ; 50

Output membership functions

Intended Direction

Table 13: Output Membership Function Shape and Points used in the Fuzzy Logic Design for Intended Heading

Membership function	Shape	Points
Medium Forward	Triangle	-25 ; 0 ; 25
Short Left	Triangle	-45 ; -22.5 ; 0
Medium Left	Triangle	-67.5 ; -45 ; -22.5
Wide Left	Trapezoid	-135 ; -112.5 ; -67.5 ; -45
Short Right	Triangle	0 ; 22.5 ; 45
Medium Right	Triangle	22.5 ; 45 ; 67.5
Wide Right	Trapezoid	45 ; 67.5 ; 112.5 ; 135

Rules

1. IF 'Intent' IS 'Left' AND 'Concentration' IS 'Very Sure' THEN 'Intended Direction' IS 'Wide Left'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

2. IF 'Intent' IS 'Left' AND 'Concentration' IS 'Sure' THEN 'Intended Direction' IS 'Medium Left'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

3. IF 'Intent' IS 'Left' AND 'Concentration' IS 'Not So Sure' THEN 'Intended Direction' IS 'Short Left'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

4. IF 'Intent' IS 'Forward' AND 'Concentration' IS 'Very Sure' THEN 'Intended Direction' IS 'Medium Forward'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

5. IF 'Intent' IS 'Forward' AND 'Concentration' IS 'Sure' THEN 'Intended Direction' IS 'Medium Forward'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

6. IF 'Intent' IS 'Forward' AND 'Concentration' IS 'Not So Sure' THEN 'Intended Direction' IS 'Medium Forward'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

7. IF 'Intent' IS 'Right' AND 'Concentration' IS 'Very Sure' THEN 'Intended Direction' IS 'Wide Right'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

8. IF 'Intent' IS 'Right' AND 'Concentration' IS 'Sure' THEN 'Intended Direction' IS 'Medium Right'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

9. IF 'Intent' IS 'Right' AND 'Concentration' IS 'Not So Sure' THEN 'Intended Direction' IS 'Short Right'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

APPENDIX B

The following are generated from LabVIEW using the Fuzzy System Designer tool of the fuzzy logic systems implemented for the human study.

Fuzzy System for Corrected Heading

The filename for this system is CorrectedFL v6.fs.

Input variables

Table 14: Input Variables in Fuzzy Logic Design for Corrected Heading

Name	**Range**	**Number of membership functions**
Intended	0 to 1	2
Left	0 to 1	2
Right	0 to 1	2
Intent	0 to 4	3

Output variables

Table 15: Output Variables in Fuzzy Logic Design for Corrected Heading

Name	**Range**	**Number of membership functions**
Corrected Heading	-12 to 12	7

Defuzzification method: Center of Maximum

Input membership functions

Intended

Table 16: "Intended" Membership Function Shape and Points used in the Fuzzy Logic Design for Corrected Heading

Membership function	Shape	Points
Near	Trapezoid	0 ; 0 ; 0.25 ; 0.75
Far	Trapezoid	0.25 ; 0.75 ; 1 ; 1

Left

Table 17: "Left" Membership Function Shape and Points used in the Fuzzy Logic Design for Corrected Heading

Membership function	Shape	Points
Near	Trapezoid	0 ; 0 ; 0.25 ; 0.75
Far	Trapezoid	0.25 ; 0.75 ; 1 ; 1

Right

Table 18: "Right" Membership Function Shape and Points used in the Fuzzy Logic Design for Corrected Heading

Membership function	Shape	Points
Near	Trapezoid	0 ; 0 ; 0.25 ; 0.75
Far	Trapezoid	0.25 ; 0.75 ; 1 ; 1

Intent

Table 19: "Intent" Membership Function Shape and Points used in the Fuzzy Logic Design for Corrected Heading

Membership function	**Shape**	**Points**
Forward	Singleton	1
Left	Singleton	2
Right	Singleton	3

Output membership functions

Corrected Direction

Table 20: Output Membership Function Shape and Points used in the Fuzzy Logic Design for Corrected Heading

Membership function	**Shape**	**Points**
No Change	Triangle	-3 ; 0 ; 3
Turn Left	Triangle	-6 ; -3 ; 0
Turn More Left	Triangle	-9 ; -6 ; -3
Large Left Turn	Trapezoid	-12 ; -12 ; -9 ; -6
Turn Right	Triangle	0 ; 3 ; 6
Turn More Right	Triangle	3 ; 6 ; 9
Large Right Turn	Trapezoid	6 ; 9 ; 12 ; 12

Rules

1. IF 'Intended' IS 'Near' AND 'Left' IS 'Near' AND 'Right' IS 'Near' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'Large Right Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

2. IF 'Intended' IS 'Near' AND 'Left' IS 'Near' AND 'Right' IS 'Near' AND 'Intent' IS 'Left' THEN 'Corrected Direction' IS 'Large Left Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

3. IF 'Intended' IS 'Near' AND 'Left' IS 'Near' AND 'Right' IS 'Near' AND 'Intent' IS 'Right' THEN 'Corrected Direction' IS 'Large Right Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

4. IF 'Intended' IS 'Near' AND 'Left' IS 'Near' AND 'Right' IS 'Far' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'Turn More Right'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

5. IF 'Intended' IS 'Near' AND 'Left' IS 'Near' AND 'Right' IS 'Far' AND 'Intent' IS 'Left' THEN 'Corrected Direction' IS 'Large Left Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

6. IF 'Intended' IS 'Near' AND 'Left' IS 'Near' AND 'Right' IS 'Far' AND 'Intent' IS 'Right' THEN 'Corrected Direction' IS 'Turn Right'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

7. IF 'Intended' IS 'Near' AND 'Left' IS 'Far' AND 'Right' IS 'Near' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'Turn More Left'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

8. IF 'Intended' IS 'Near' AND 'Left' IS 'Far' AND 'Right' IS 'Near' AND 'Intent' IS 'Left' THEN 'Corrected Direction' IS 'Turn Left'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

9. IF 'Intended' IS 'Near' AND 'Left' IS 'Far' AND 'Right' IS 'Near' AND 'Intent' IS 'Right' THEN 'Corrected Direction' IS 'Large Right Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

10. IF 'Intended' IS 'Near' AND 'Left' IS 'Far' AND 'Right' IS 'Far' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'Turn More Right'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

11. IF 'Intended' IS 'Near' AND 'Left' IS 'Far' AND 'Right' IS 'Far' AND 'Intent' IS 'Left' THEN 'Corrected Direction' IS 'Turn More Left'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

12. IF 'Intended' IS 'Near' AND 'Left' IS 'Far' AND 'Right' IS 'Far' AND 'Intent' IS 'Right' THEN 'Corrected Direction' IS 'Turn More Right'

connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

13. IF 'Intended' IS 'Far' AND 'Left' IS 'Near' AND 'Right' IS 'Near' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'No Change'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

14. IF 'Intended' IS 'Far' AND 'Left' IS 'Near' AND 'Right' IS 'Near' AND 'Intent' IS 'Left' THEN 'Corrected Direction' IS 'Large Left Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

15. IF 'Intended' IS 'Far' AND 'Left' IS 'Near' AND 'Right' IS 'Near' AND 'Intent' IS 'Right' THEN 'Corrected Direction' IS 'Large Right Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

16. IF 'Intended' IS 'Far' AND 'Left' IS 'Near' AND 'Right' IS 'Far' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'Turn Right'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

17. IF 'Intended' IS 'Far' AND 'Left' IS 'Near' AND 'Right' IS 'Far' AND 'Intent' IS 'Left' THEN 'Corrected Direction' IS 'Large Left Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

18. IF 'Intended' IS 'Far' AND 'Left' IS 'Near' AND 'Right' IS 'Far' AND 'Intent' IS 'Right' THEN 'Corrected Direction' IS 'No Change'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

19. IF 'Intended' IS 'Far' AND 'Left' IS 'Far' AND 'Right' IS 'Near' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'Turn Left'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

20. IF 'Intended' IS 'Far' AND 'Left' IS 'Far' AND 'Right' IS 'Near' AND 'Intent' IS 'Left' THEN 'Corrected Direction' IS 'No Change'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

21. IF 'Intended' IS 'Far' AND 'Left' IS 'Far' AND 'Right' IS 'Near' AND 'Intent' IS 'Right' THEN 'Corrected Direction' IS 'Large Right Turn'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

22. IF 'Intended' IS 'Far' AND 'Left' IS 'Far' AND 'Right' IS 'Far' AND 'Intent' IS 'Forward' THEN 'Corrected Direction' IS 'No Change'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

23. IF 'Intended' IS 'Far' AND 'Left' IS 'Far' AND 'Right' IS 'Far' AND 'Intent' IS 'Left'

THEN 'Corrected Direction' IS 'No Change'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

24. IF 'Intended' IS 'Far' AND 'Left' IS 'Far' AND 'Right' IS 'Far' AND 'Intent' IS 'Right'
THEN 'Corrected Direction' IS 'No Change'
connective: AND (Minimum) ; implication: Minimum ; degree of support: 1.00

APPENDIX C

The following are results collected during the human study. The values including the averages, standard deviations, run totals, maximum, minimum values.

Table 21: Total Training Session Time Statistics

Average	Standard Deviation	Maximum	Minimum
10.44	4.72	17.00	5.83

Table 22: Time per Run Statistics

Time per Run					
Control Mode	**Command Mode**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**
Manual Control	Speech	188.58	33.41	271.41	110.04
	EEG	67.84	16.04	94.92	40.31
	Multimodal	78.61	6.76	86.88	65.39
	Average per Run	133.26	62.73	271.41	40.31
Autonomous Control	Speech	140.54	88.19	439.64	45.85
	EEG	93.71	99.79	399.76	41.66
	Multimodal	93.90	68.00	263.39	40.06
	Average per Run	112.68	89.80	439.64	40.06
Fuzzy Logic Autonomous Control	Speech	156.84	72.94	377.88	68.59
	EEG	68.12	30.94	131.64	41.37
	Multimodal	63.78	24.04	126.58	40.70
	Average per Run	98.93	66.46	377.88	40.70

Table 23: Distance Travelled (Left Wheel) Statistics

Distance Travelled Based on Left Motor Encoder Counts					
Control Mode	**Command Mode**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**
Manual Control	Speech	9.25	0.97	10.45	6.28
	EEG	9.14	0.43	9.71	8.46
	Multimodal	9.31	0.73	10.68	8.43
	Average per Run	9.24	0.82	10.68	6.28
Autonomous Control	Speech	20.32	14.38	71.47	7.98
	EEG	18.60	22.98	95.92	8.49
	Multimodal	15.95	10.90	46.41	8.41
	Average per Run	18.53	16.84	95.92	7.98
Fuzzy Logic Autonomous Control	Speech	23.52	13.79	64.55	8.13
	EEG	14.41	7.73	25.83	8.67
	Multimodal	10.11	3.61	22.96	8.59
	Average per Run	15.53	10.89	64.55	8.13

Table 24: Distance Travelled (Right Wheel) Statistics

Distance Travelled Based on Right Motor Encoder Counts					
Control Mode	**Command Mode**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**
Manual Control	Speech	9.29	0.87	10.60	7.11
	EEG	9.20	0.36	9.76	8.58
	Multimodal	9.15	0.82	10.48	7.87
	Average per Run	9.23	0.78	10.60	7.11
Autonomous Control	Speech	19.68	11.96	53.22	8.19
	EEG	19.83	26.60	104.32	8.42
	Multimodal	16.65	14.57	59.41	8.29
	Average per Run	18.85	18.40	104.32	8.19
Fuzzy Logic Autonomous Control	Speech	22.78	10.41	50.95	8.14
	EEG	12.76	5.58	21.06	8.56
	Multimodal	9.30	2.45	18.42	8.28
	Average per Run	14.60	9.08	50.95	8.14

Table 25: Frequency of Total Commands Executed per Run Statistics

Commands Delivered					
Control Mode	**Command Mode**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**
Manual Control	Speech	12.73	1.84	15.00	8.00
	EEG	45.67	17.64	68.00	19.00
	Multimodal	44.88	14.77	79.00	31.00
	Average per Run	28.41	19.74	79.00	8.00
Autonomous Control	Speech	7.33	4.38	20.00	2.00
	EEG	58.25	56.50	216.00	14.00
	Multimodal	55.20	51.57	200.00	7.00
	Average per Run	36.81	48.45	216.00	2.00
Fuzzy Logic Autonomous Control	Speech	7.86	3.54	16.00	3.00
	EEG	44.08	23.84	104.00	19.00
	Multimodal	41.07	28.12	110.00	16.00
	Average per Run	28.41	24.68	110.00	3.00

Table 26: Speech Commands Received per Run Statistics

Speech Commands Received					
Control Mode	**Command Mode**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**
Manual Control	Speech	12.73	1.84	15.00	8.00
	EEG	0.00	0.00	0.00	0.00
	Multimodal	1.00	1.05	3.00	0.00
	Average per Run	3.52	5.14	15.00	0.00
Autonomous Control	Speech	7.33	4.38	4.38	20.00
	EEG	0.00	0.00	0.00	0.00
	Multimodal	1.43	1.86	7.00	0.00
	Average per Run	1.89	2.93	16.00	0.00
Fuzzy Logic Autonomous Control	Speech	7.86	3.54	16.00	3.00
	EEG	0.00	0.00	0.00	0.00
	Multimodal	0.87	1.56	5.00	0.00
	Average per Run	1.97	2.93	11.00	0.00

Table 27: Cognitive Commands Received per Run Statistics

Cognitive Commands Received					
Control Mode	**Command Mode**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**
Manual Control	Speech	0.00	0.00	0.00	0.00
	EEG	5.83	2.79	8.00	0.00
	Multimodal	5.75	4.76	12.00	0.00
	Average per Run	2.79	4.03	12.00	0.00
Autonomous Control	Speech	0.00	0.00	0.00	0.00
	EEG	5.50	7.56	30.00	0.00
	Multimodal	4.80	11.73	48.00	0.00
	Average per Run	3.08	7.99	48.00	0.00
Fuzzy Logic Autonomous Control	Speech	0.00	0.00	0.00	0.00
	EEG	3.58	4.01	15.00	0.00
	Multimodal	3.13	6.45	26.00	0.00
	Average per Run	1.95	4.42	26.00	0.00

Table 28: Facial Commands Received per Run Statistics

Facial Commands Received					
Control Mode	**Command Mode**	**Average**	**Standard Deviation**	**Maximum**	**Minimum**
Manual Control	Speech	0.00	0.00	0.00	0.00
	EEG	39.83	12.28	63.00	20.00
	Multimodal	37.50	12.28	63.00	20.00
	Average per Run	18.59	21.66	63.00	0.00
Autonomous Control	Speech	0.00	0.00	0.00	0.00
	EEG	52.75	53.55	216.00	12.00
	Multimodal	47.53	45.19	194.00	3.00
	Average per Run	29.94	45.64	216.00	0.00
Fuzzy Logic Autonomous Control	Speech	0.00	0.00	0.00	0.00
	EEG	40.50	20.59	89.00	17.00
	Multimodal	36.20	28.63	109.00	3.00
	Average per Run	24.76	26.06	109.00	0.00

Table 29: Run Totals

	Command Mode	**Run Totals**
Manual Control Completed Runs	Speech	15
	EEG	6
	Multimodal	8
	Average per Run	29
Autonomous Control Completed Runs	Speech	21
	EEG	16
	Multimodal	15
	Average per Run	52
Fuzzy Logic Autonomous Control Completed Runs	Speech	14
	EEG	12
	Multimodal	15
	Average per Run	41
All Completed Runs	Speech	50
	EEG	34
	Multimodal	38
	Total	122
Total Runs	Speech	57
	EEG	46
	Multimodal	51
	Total	155