Development of an EEG signal based Brain Machine Interface for a Meal Assistance Robot

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Degree of Master of Science

Department of Mechanical Engineering

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Thesis submitted in partial fulfillment of the requirements for the degree Master of Science in Biomedical Engineering

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DECLARATION

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Abstract

Most of the countries in the world are facing the problems of aging population and disabilities among the population. Among different problems faced by these individuals, self feeding can be identified as an important aspect that should get more attention from the research community. In addition, self feeding reflects the interdependency of an individual and thus relate to their mental health. Taking care of these individuals using care takers is becoming more and more difficult due to diminishing workforce for such tasks. Therefore assistive robotic technologies play a major role in providing feeding solutions to these individuals with disabilities. Meal assistance robot is a device designed to assist the individuals in need with self feeding.

The research work of this thesis is focused on developing an EEG signal based Brain Machine Interface for a meal assistance robot. Meal assistance robot is capable of handling solid food items using the spoon mounted on the end effector. Identifying user's food selection is carried out using a Steady State Visually Evoked Potential based Brain Machine Interface where 3 LED matrices flicking at 6Hz, 7Hz and 8Hz are used to generate the stimulations in the brain. User has to gaze at a LED panel to activate the motion path of the robot which will feed the solid food from the container associated with the gazed LED panel. System is incorporated with a visual servoing algorithm to identify the user's mouth position and adapt the food feeding location according the mouth location. Further, Mouth open/close status detection system is developed to measure the user's willingness to intake the food. The developed meal assistance robot is experimentally validated using 15 subjects in different experiments.

After detailing the research methods carried out, discussion of the results obtain are presented at the end of the thesis with limitations of the research and possible future improvements.

***Keywords*-Meal Assistance Robot, SSVEP, visual servoing, EEG**

DEDICATION

This dissertation is dedicated to my parents, to whom i can trace my every success to.

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LIST OF ABBREVIATIONS

FFT Fast Fourior Transformation

CCA Canonical Correlation Analysis

ADL Activities of Daily Living

SSVEP Steady State Visually Evoked Potential

EEG Electroencephalography

FMRI Functional Magnetic Resonance Imaging

MRI Magnetic Resonance Imaging

DOF Degree of Freedom

SCI Spinal Cord Injury

TMR Targeted Muscle Reinnervation

ECoG Electrocorticography

EMG Electromyography

EOG Electrooculography

BMI Brain Machine Interface

fNIRS Functional Near-Infrared Spectroscopy

SSVEP Steady State Auditory Evoked Potential

ERP Event Related Potential

Chapter 1

INTRODUCTION

According to 2011 world bank's report on disability, nearly one billion people around the world is suffering from some form of disability. From that, 110 million to 190 million people are suffering from significant disabilities [3]. Recent report from institute on disability, University of New Hampshire [4] indicate a increase in percentage of people with disabilities in the US population from 11.9% in 2010 to 12.8% in 2016. World Health Organization indicate that this situation is more severe in 3rd world countries. Furthermore United Nations report on World Population Ageing [1] predict that aged population will almost triple in next 35 years [Fig.1.1]. All of the statistics and predictions suggest that disabilities among the population will be one of the major problems that needs to be addressed by future generations.

Having a severe disability will limit a person's ability to perform day today activities and most importantly, Activities of Daily Living (ADL). These ADLs include six basic activities, eating bathing, dressing, transferring, toileting and continence. Depending on the level of disability, a person may not be able to do one or more of these activities according to their will. That is when the importance of assistive devices become prominent and a necessity for the well being of people in need. Among many assisitive devices that are designed to cater the needs of disabled people, meal assistance robots can be considered as a less researched area. Even though there are few commercially available devices such as meal budy [5], Obi [6] and bestic arm [7], they are unable to fulfill the needs of people having severe disabilities. This is due to the controlling methods/ user

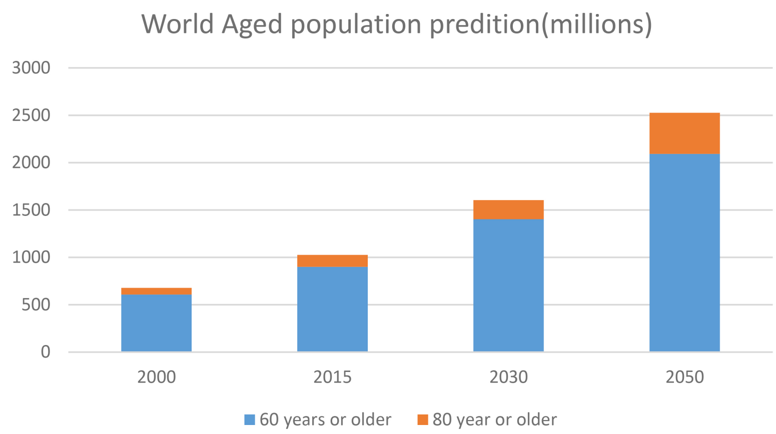


Figure 1.1: World population projection for the period up to 2050 [1].

intention detection methods used by the feeder arms. Most of the feeder robots use button operation as the main controller method and this require the user to have some degree of limb function to operate the robot. But people with severe disabilities have little or no limb functions to control the feeder robot according to their will.

Furthermore, all most all of the meal assistance robots use fix point feeding method. At the beginning device should be calibrated according to the user's height. Then, the device will feed the food to that fixed location continuously. By using this method user need to be in the same location for the whole feeding process and it will be uncomfortable for the user to stay at the same location throughout the feeding process. This research was motivated by the need to find possible solution to overcome those disadvantages of existing meal assistance robots.

Moreover, brain signals can be identified as one of the potential control signals that researches can incorporate in assistive devices. Human brain is the most complex and mysterious organ in the human body and scientist are yet to discover the full capabilities of it. Also no scientific method is yet been successfully able to identify and explain the complex nature of the human brain. But brain is among the interests of researches from Egyptian era. Lack of proper scientific techniques and technologies prevented anyone from properly understanding the brain. With the introduction of the modern neuroscience, scientists are able to accurately identify the basic functions of the brain. Invention of technologies like Functional Magnetic Resonance Imaging (FMRI) and Magnetic Resonance Imaging (MRI) helped to get more insight in to the brain.

Even though neuroscience was existed for centuries, controlling a robot using thoughts was only limited to frictional arts. Even after the discovery of electrical phenomena of the brain (Later named and electroencephalography or EEG) by Hans Berger in 1927, it took nearly 100 years to successfully implement systems that are controlled by human thoughts.

Electroencephalography (EEG) is the method that is used to record the electrical activity of human brain. Today scientists use EEG signals to monitor human brain as well as control robotic devices or software. Some of the applications of EEG include control of assistive devices, monitoring mental conditions, brain speller etc . In an ideal conditions EEG can be identified as the perfect signal to be used in controlling applications such as assistive devices. But the current brain technology is at it's primary state and still unable to provide complex signals needed in complex control tasks. In the current stage researches are pursuing the possibility of using EEG phenominas like Event Related Potential and Event Related De/Synchronization. One of the prominent event related potential is called Steady State Visually Evoked Potential (SSVEP).

This research intend to perceive the capability of using Steady State Visually Evoked Potential (SSVEP) as a control signal to identify the user intention to control a meal assistance robot. Additionally visual guidance of the meal assistance robot is also researched in order to facilitate the feeding process. SSVEP is the signal generated in the brain due to external visual stimuli. In this research 3 visual stimuli were used to select between 3 different solid food items.

1.0.1 Contributions of the Thesis

Research work presented in this thesis addresses the process of development and control of a meal assistance robot using Steady State Visually Evoked Potential signals. Furthermore, this thesis discuss the use of visual servoing techniques to find and feed food according to the location of the user's mouth. Major contributions of this thesis can be outlined as follows:

- Design and fabricate a 4DOF meal assistance robot capable of handling multiple food items. Meal assistance robot is a servo based robot and the setup include 3 food bowls user to select from.
- Develop an effective user intention detection method based on EEG - SSVEP signals using FFT and CCA to identify the required food selection of the user.
- Develop a visual servoing method to identify the mouth locations of the user and feed according to that location. In addition, a method capable of identifying the willingness of the user to consume the food is proposed considering the user's mouth open/close conditions.
- Evaluation of the system using healthy subjects to validate the overall system.

1.0.2 Thesis Overview

The thesis consists of seven other chapters to elaborately present the research work carried out related to the topic. Contents of each chapter can be summarized as below.

Chapter 2: Literature Review

This chapter discuss the design and control features of most of the existing meal assistance robots in both commercial stage and research stage. Also it discuss the use of Electroencephalography (EEG) as a control signal to control the meal assistance robot. Initially, literature on existing meal assistance robots are discussed under their mechanical design and controlling methods. Control methods are discussed under different user intention identification methods and the hardware controlling of the robot. Finally use on brain machine interface as a control method is discussed. Brief summery of emerging technologies is discussed at the end of the chapter.

Chapter 3: Overview of the proposed meal assistance robot and hardware design of the 4DOF manipulator

Overall design and controlling of the proposed meal assistance robot is discussed under the first section of this chapter. Experiment setup is discussed along with the main control algorithm used to identify the user intention and control the meal assistance robot. Second section of this chapter is allocated to discuss the hardware design of the 4DOF manipulator used in the meal assistance robot. Forward and inverse kinematics of the system is presented with derived solutions. Then, controlling method used to control the meal assistance robot is discussed in later sections.

Chapter 4: Development of user intention detection method using EEG:SSVEP based BMI

Using Steady State Visually Evoked Potential to identify the user intention is discussed in this chapter. Details related to stimuli generation, stimuli frequency selection, EEG acquisition, Fast Fourier Transformation based classification, and Canonical Correlation Analysis based classification are discussed in separate subsections.

Chapter 5: Vision based mouth position identification and mouth open/close detection

This chapter discuss the proposed vision based mouth position identification and mouth open/close identification method. Use of a wide angle camera with OpenCV based Haar classifier to identify the mouth within the image frame and use of OpenCV based custom trained classifier to identify mouth opening is discussed in detail.

Chapter 6: Experiments, results and discussion

Experiments, results and discussion chapter of this thesis describe the experimental procedures carried out to validate the system, results obtained using the experiments and a discussion of the obtained results. Four separate set of experiments are discussed to validate the FFT based classification method, CCA based classification method, mouth tracking algorithm and mouth open/close status detection algorithm. Further, data from user satisfaction survey is presented and discussed in this chapter.

Chapter 7: Conclusion and future work

Final chapter of this thesis presents the conclusion of the research work carried out in this thesis. Further, possible future improvements of the system is discussed at the end of this chapter.

Chapter 2

LITERATURE REVIEW

Self-feeding is one of the basic human activity and it's among the ADLs in day today life. Usually assistance of a caretaker is needed for the feeding of individuals who are having severe disabilities such as spinal cord injury (SCI), quadriplegia and limb disarticulations. But it is becoming more and more difficult to find human workforce for caretaking. If the patient is not able to use adapted cutlery and crockery, three different solutions can be found in the literature to solve the problem of self-feeding. These are manually operated eating systems, electrically operated eating systems and forearm supports and stabilizers. To use manually operated eating systems and forearm supports patient need at least partial control over their upper limbs. This is evident in forearm support systems like Multilink dynamic arm [8] and manual meal assistance systems like Nelson eater [9]. Use of these systems are not reliable and also it will affect the comfortability of the patient. In light of these issues, focus has been given towards developing Electrically powered meal assistance robots suitable for those individuals. This section of the thesis is to review on meal assistance robots that have been proposed and/or developed to date, and to identify important design features, advantages and limitations of such systems. Overview of the meal assistance robots that discussed in this section is listed in the Table 2.

Primary objective of a meal assistance robot is to assist or help in the self-feeding process of a particular individual who do not have enough capacity to feed himself/herself using his/her upper-limb. Even though there are no standardized components of a meal assistance robot, a meal assistance robot basically consists

Feeder robot	**Country**	**DOF**	**Research/ Commercial**
My Spoon [10]	Japan	5	Commercial
Bestic arm [7]	Sweden	4	Commercial
Mealbuddy [5]	Canada	4	Commercial
Winsford™ Feeder system [11]	USA	2	Commercial
Mealtime Partner [12]	USA	2	Commercial
The VoiceBot [13]	USA	4	Research
Assistive Robotic Arm by University of the Ryukyus [14]	Japan	7	Research
Meal Support by Shizuoka University [15]	Japan	5	Research
Chopstick-Equipped Meal Assistance Robot [16]	Japan		Research
Eye-Operated Meal Assistance Robot by Yamaguchi university [17]	Japan	2	Research
ICRAFT [18]	USA	4	Research
ASIBOT [19]	Spain	5	Research
Meal Support system by Saga University [20]	Japan	4	Research
JACO robot arm based meal assistance systems [21]	Canada	6	Commercial
Hello Spoon [22]	Mexico	4	Crowd funded
Handy 1 [23]	USA	*	Research
Obi meal assitstance robot [6]	USA	6	Commercial
Self-Feeding Assistive Robot by Korea National Rehabilitation Research Institute [24]	Korea	2	Research

* Handy -1 is a multipurpose robot which include plate washing, shaving and teeth cleaning integrated in to the system.

Table 2.1: Overview of meal assistance robots

of a robot arm or feeding mechanism, control hardware to drive that robot or mechanism, a command algorithm and sensors to capture the human motion intension.

Meal assistance robots that have been developed up to date can be classified simply in to research or commercial products as mentioned in the table 2. When developing a meal assistance robot, it is necessary to concern about the user intention identification method, safety and comfort of the user, range of the robot arm, and speed of the operation. Otherwise meal assistance robots might not be effective for patients who suffer serious disabilities. Different hardware setups and control algorithms have been used in existing meal assistance robots to achieve those required goals. Literature can be mainly categorized under the topics of Mechanical design and intention detection system to better understand the existing meal assistance systems.

2.1 Mechanical design of meal assistance robots.

Many different factors affect the mechanical design of meal assistance robots. Food feeding method, food storage method, actuation method, control method are some of the major factors to be considered. Assessment of these factors is important in designing a meal assistance robot to achieve a user friendly and economical design. This section will discuss in detail about the factors that needed to be considered when designing a meal assistance robot and the implementation of those factors in existing meal assistance robots.

2.1.1 Feeding methods

Among many different factors that should be considered when designing a meal assistance robot, one of the main factors to consider is the feeding method. Different types of feeding methods are used to feed different patients according to their disability. Basically tube feeding and oral feeding are the mostly used feeding methods for disabled patients. Tube feeding is a method of giving necessary nutrition to the body as liquid form of nourishments. It contains the nutrients needed on daily basis such as carbohydrates, proteins, fat, vitamins, minerals and

(a) (b)

Figure 2.1: (a) Tube feeding (b) Spoon feeding

water. Food is delivered to the body using nasogastric tubes that goes from nose to the stomach or to the small intestine. However, tube feeding method is used for patients who have serious brain injuries and cannot control the muscles in mouth voluntarily or who are unconscious due to the injury.

Oral feeding is the process of talking food by mouth. Generally conscious patients always prefer oral feeding methods. However disabled patients need some externally assisted feeding methods instead of their own hands. Spoon is the most common external feeding device used in oral feeding methods. Also spoon based feeding method is the mostly used method in existing feeder robots. Handy - 1 [23], Winsford feeder [11], meal buddy [5], My spoon [10], Neater eater [25], Obi meal assistance system [6] and Mealtime partner [12] dining system are some of the best examples for commercially produced meal assistance robots having a spoon based feeding method. However, there are some feeder arms that were designed to feed using other methods. Self-feeding assistive robot which was designed by Korea National Rehabilitation Research Institute has both gripper and spoon for the feeding purpose [24]. Meal assistance robot developed in Tokai University, Japan [16] uses a chopsticks based feeder system. But spoon based feeding method is the most convenient and effective one to be used with disabled patients.

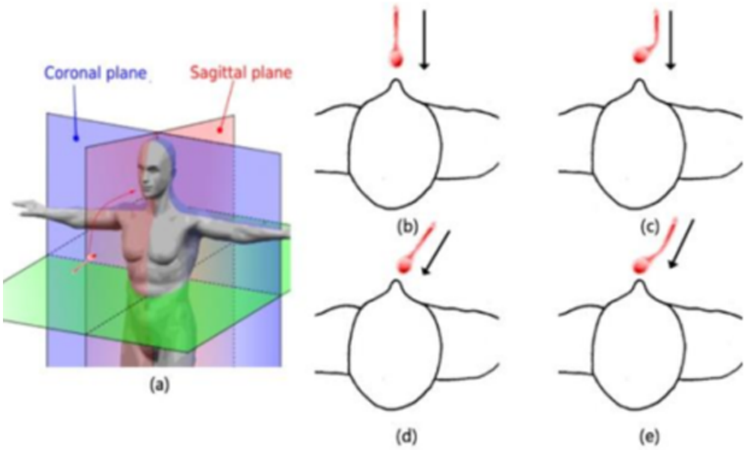


Figure 2.2: Spoon approaching modes. (a) The sagittal plane on which a spoon moves. (b), (c),(d), and (e) represent the top view of a spoon when a robot approaches a user's mouth. The red object means a spoon. (c), (d) and (e) are more comfortable then (b) (adopted from [24])

Feeding mechanism of the spoon based feeding devices is critical in terms of the safety and comfortability of the patient. When feeding, spoon should tilt to the user's mouth in order to unload the food on the spoon easily when the spoon arm is positioned in the user's mouth. Technically, the spoon should tilt to users with disabilities. If the self-feeding robot does not have a tilting function, then the user will struggle to eat the food on the spoon. On the other hand it is very important to consider about the spoon moving path or trajectory planning of the feeder robot arm, as it should be comfortable for the patient. Fig 2.2 illustrate different methods of spoon approaches. If the spoon approaches from the side of user's mouth, then a user can feel safer. This is because those motions are similar to most people's motions when they actually eat foods [23, 24].

2.1.2 Food storage method

Food storing is another important factor to be considered. This is because proper storing method is required to avoid the wastage, improve the safety and improve the efficiency of the feeder system. Most of the wastage in a feeder arm occur during the collection of the food. Therefore, it is required to have

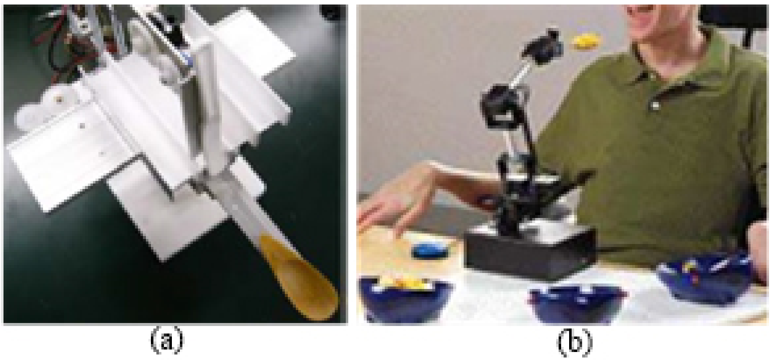


Figure 2.3: Foods storing methods. (a) The foods tray with tracks [17]. (b) Quadrant platform used in meal buddy [5].

proper storage method to avoid unnecessary wastage of foods. On the other hand, storing arrangement should consist of a facility to store several foods. When considering the existing meal assistance robots, different foods storing methods have been used. As shown in Fig. 2.3 (b), the meal buddy was designed with special platform which has a shape of quadrant [5]. In this method spoon should be controlled to move to each and every dish for collect the foods. Using the quadrant method it is possible to provide the user with different food items to select. Because of this, most of existing feeder robots have the same method to store foods. However, the meal assistive robot designed by Yamaguchi University use different method for food collecting. This robot was made with food storing tray which consist of five tracks and shutters as shown in Fig.2.3 (a). This mechanism is used to push the foods on to the spoon through the track [17]. Even though this method is simple, when compared with other feeder arm designs there are few drawbacks to be highlighted. Especially in this method there could be considerable wastage of food since they are pushed on to the spoon from the tracks. Other issue is the movement of the spoon through the sagittal plane of the patient. As discussed in above it may feel uncomfortable for the patients.

2.1.3 Actuation methods used in meal assistance robots

Actuation method is responsible of providing reliable motion outputs to the meal assistance robot. It should be able to achieve smooth motions in order to feed food without wastages due to spilling. Generally, different types of actuation methods are used to produce linear and rotational movements of robot arms. Pneumatics, hydraulic and electrical actuators are the most commonly used actuation methods in robotics. However, meal assistance robots can be categorized into special category since the whole system is used for assistive purpose of disabled patients. Therefore, the pneumatic and hydraulics is not a suitable actuation methods as pneumatic and hydraulics are typically used in industrial purposes which needs high forces. Also hazardous nature of those methods limit them from using in assistive robotics. Hence meal assistance robots are designed with electrical actuation systems which provide more accurate and smooth controlling [5–7, 10]. Since actuation should be done in a safe manner, the DC and servo motors have mostly been used to control the feeder arm motions [26]. DC motors also help to move the arm smoothly to avoid the unnecessary wastage of the foods. The Handy1 [23], my spoon [10], neater eater [25] and other feeder arms have been designed with DC motors. This shows the applicability of DC motors for the feeder arms in meal assistance robots. However, the Meal buddy is operated by using servo motors in each joint [5]. Even though servo motors are not smooth as DC motors in operation, they have a competitive advantage in cost and controlling. Table 2.2 lists the popular feeder arms with respective to control method used.

2.1.4 Summary

From the table 2 it can be figured out that most of the existing meal assistance robots in both the commercial and research stages have used robot arms having 4 degrees of freedom (DOF) or more. In those systems, a spoon is attached as the end effector and food is scooped, then fed to the user using the spoon. Most of the systems were capable of handling solid food items while some were able to handle liquid based food items as well. Each joint of the robot arm is controlled using DC or servo motors. Geared motors are used to get smooth motions by reducing the speed of the motors. Also most of the robot arms use a food storage system similar to quadrant method [5] allowing the user to select from few different food items.

Table 2.2: Control methods of existing meal assistance robots.

Feeder robot	**Input type**	**Special remarks**
My Spoon [10]	Keyboard/joystick	Chin controlled joystick
Bestic arm [7]	Keyboard/joystick	
Mealbuddy [5]	Keyboard/joystick	
Winsford™ Feeder system [11]	Keyboard/joystick	Joystick controlled by head
Mealtime Partner [12]	Keyboard/joystick	
The VoiceBot [13]	Voice commands	Nonverbal voice command
Assistive Robotic Arm by University of the Ryukyus [14]	Keyboard/joystick	Vision system is used to positioning
Meal support system by Shizuoka University [15]	Keyboard/joystick	Laser Range Finder is used to identify the food positions
Chopstick-Equipped Meal Assistance Robot [16]	Hands free pointing	Reflector is used to track head moments and ultimately the mouse pointer
Eye-Operated Meal Assistance Robot by Yamaguchi university [17]	Eye Interface	
ICRAFT [18]	Eye tracking	Eye tracking interface
ASIBOT [19]	Keyboard/joystick	Use of docking concept for multiple uses
Hello Spoon [22]	Keyboard/joystick	
Handy 1 [23]	Keyboard/joystick	Possible to achieve several everyday functions such as eating, cleaning teeth, drinking and shaving

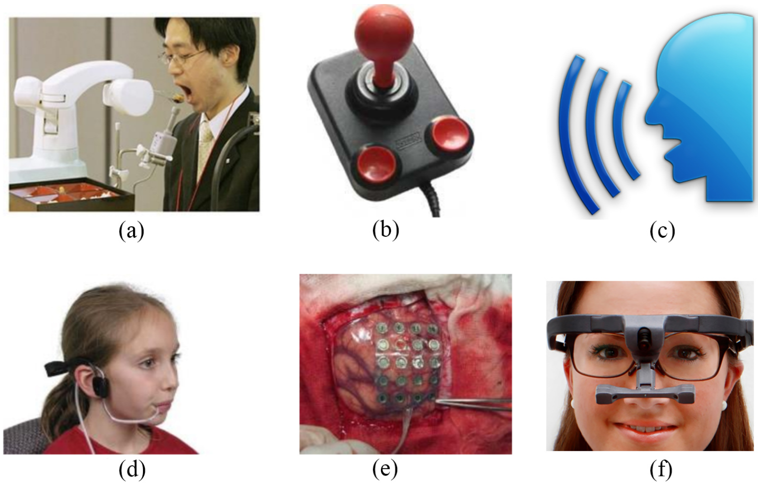


Figure 2.4: Different input signals. (a) Head controlled joystick [10] (b) Joystick (c) Voice control , (d) Sip and puff switch [27] (e) Electrocorticography, (f) Eye tracking.

2.2 Controlling methods of meal assistance robot.

User intention detection and hardware control of the robot according to user intention can be identified as the two main stages of controlling meal assistance robots. User intention detection method will determine the user group of the meal assistance robot. For instance, patients who are suffering spinal cord injuries will not have the ability to control a button operated meal assistance robot. Other methods of user intention identification should be implemented in such situations. After identifying the correct intention, robot should be correctly controlled to feed the food. While few different methods can be used to actuate the robot it is important to identify a viable solution.

2.2.1 User input identification methods used in meal assistance robots.

There are many types of input signals such as joystick signals, sip and puff switches, eye movement sensors (as shown in Fig. 2.4) that have been used for controlling of meal assistance robots. Table 2.2 summarizes the widely used input signals and methods for controlling meal assistance robots.

Customized keyboard and joysticks are the main input method used in meal assistance robots. Almost all the feeder arms have the ability to pre-program the mouth positions and the bowl positions, keyboard or joystick is only used to initiate the feeding motion and selecting food. These keyboard and joysticks are fabricated according to the subject's disability. Manus robot [28] developed in 1996 uses different input methods like foot controlled keyboard, chin joystick with sip and puff switches, and foot joystick to obtain user inputs. These input methods are used by many commercial meal assistance robots as their control method. My spoon feeder arm [10] uses the chin controlled joystick to allow their users to control the meal assistance robot. Meal Buddy feeder arm [5] is implementing the one button control method for the user input detection and it will feed the food to the pre initialized position. Systems like Bestic Arm [7], Winsford Feeder [11], Mealtime Partners Dining System [12], and JACO robot arm [21], ASIBOT [19] also uses the keyboard and joystick input method. This method is easy to incorporate with different patients according to their disability. As an example if the patient has an upper limb disarticulation, a joystick can be design to work operate from lower limbs. But in a case of SCI patients, using a joystick is not possible when they have no control over their limbs. In situations where patients having C4 or above level spinal cord injuries, using a neck controlled joystick is also not a possibility.

Northeastern University has developed a 4 axis feeder arm [18] which is capable of working independently once it is configured initially. User is given the opportunity to choose between three bowl positions, initiating and concluding of the feeding process is done by displaying the related positions on a screen. IR light is shined on the subject's eyes and glow is reflected back to the camera, this is used to track the eye moments when user is selecting an option using their eye. Open source software called ITU Gazetracker is used to track the moments in the eye. Also Meal-assistance robot developed by Yamaguchi University [17] has used an eye interface for controlling the arm and selecting the food items. In this method there is a possibility that eye blinks and other moments in the eye might affect the overall system. However, properly developed system which uses this method will benefit the patient since the system can be operated with less effort.

Voice controlled method is another effective control method to be used by patients with motor disabilities or amputations. The VoiceBot [13] has used a non-verbal voice control method to obtain the control signals. User relies on continuous sounds that can vary in pitch, vowel quality, or amplitude to provide control of computer applications and ultimately the robot arm. Even though it was difficult to find similar researches for meal assisting applications, there are voice controlled robot arms designed to perform other tasks like medical surgery [29], packing, and pick and place [30]. However, the major drawback of the voice recognition when using for meal assistance robots is the fact that user needs to operate the system while eating the food. Therefor nonverbal voice recognition system might be more suitable for this method than a verbal voice recognition system.

Another control method that can be used as a control input for disabled patients is the hand free pointing devices, which can be point out which food they want and initiate the feeding action of the arm. Chopstick-equipped meal assistance robot developed by the Tokai University [16] has used this concept to select the food to be consumed by the user.

Biological signals are another type of signals that can be used as input signals for meal assistance robots. However, Electromyography (EMG) based researches are less because acquiring EMG from SCI patients is less affective with their condition. EMG signal based robot arms can be designed to operate by patients with upper limb disarticulation [31]. Also researches can be found on prostheses that use targeted muscle reinnervation (TMR) [32] and few Electrocorticography (ECOG) signal based prostheses [33, 34] which give the patient the capability of handling most ADL tasks that requires upper limbs. Both ECOG and TMR has high technological requirements. Also high costs are involved when performing surgical operations on patients to place an ECOG sensor array and to do the TMR operations. Because of these reasons ECOG and TMR are not widely popular among researches at this moment. Electrooculography (EOG) signals also can be used to identify the user intention [35]. User's eye ball movements and blinking patterns are used to select food options and start the feeding process.

2.2.2 Hardware control of the meal assistance robots.

After identifying the user intention, food should be fed to user's mouth efficiently. Two main methods can be identified from the literature to achieve this. Most common method used by all most all commercial meal assistance robots is the fixed point feeding [5, 5–7]. In this method food is scooped and fed using pre-determined motion paths. Because of this user should remain in the same location during the feeding process. Otherwise spoon's end location and mouth location won't be same and user won't be able to get the food. At the beginning of the feeding process, device should be calibrated to indicate the user's mouth location. Control system will generate a motion path according to the given mouth location and it will be used throughout the feeding process.

Adaptive feeding methods are being researched to find solutions that will solve the problem discussed above. Mostly vision based systems are used in conjunction with button or joystick controllers. Vision is used to identify the food positions and the path of the robot arm. Vision based robot arm designed by the University of the Ryukyus, Japan [14] has used a web camera to identify the water bottle kept at a table and fetch it to the patient. Same function can be achieved by other sensing methods like laser range finders, IR sensing etc. Meal support system designed by the Shizuoka University, Japan [15] has used a laser range finder to locate the food on a bowl and scoop it using the manipulator. Wheelchair-mounted robotic arm designed by the University of Massachusetts Lowell [36] has used a stereo camera to identify an object and direct the robot arm on to the object and return it to the patient. Similar system can be used in meal assistance robot to detect food items according to the favor of the individual.

2.2.3 Emerging technologies in meal assistance robots.

As the advancement of technology, new control methods are introduced and they can be adopted to existing meal assistance robot designs. By adopting these technologies accuracy and reliability can be improved for the meal assistance robots. For an example, the problem of food spilling when using the robot arms in meal assistance robot has been addressed [37]. In that paper, the team has given a computational fluid dynamic simulation of the stabilizing process and it has been experimentally proved using a 6 DOF robot arm. Journal article by University of Toronto [38] discuss the use of 3d depth sensing using Kinect sensor for meal time assistance. User's facial expressions was monitored to provide cognitive assistance during the meal consumption.

Research by Nara Institute of Science and Technology [39] discuss the use of vision based calorie counting application for smartphones. Calorie/nutrition monitoring methods can be incorporate with meal assistance robots to monitor the intake of the user and assist the nutritionist in determining meal plans. Furthermore, safety of meal assistance robot is an another important aspect in designing the robot. It should not injure or miss operate during the usage. Collision avoidance methods/ compliant control methods can be incorporated with meal assistance robots to increase the safety and user friendliness of robots. Methods such as current sensing, mechanical safety systems [40], image processing and sensor fusion [41] can be used as compliant control methods for meal assistance robots.

2.2.4 Use of Brain Machine Interfacing as a control signal.

Brain Machine Interface (BMI) is the concept of extracting neural information from the brain and translating that information to control a hardware. Main aim of using BMI is to replace or restore useful body functions of people suffering from neuromuscular disorders such as Spinal Cord Injuries(SCI), stroke, cerebral palsy and amyotrophic lateral sclerosis. BMI can be mainly identified under two categories of invasive BMI and non-invasive BMI. Invasive brain machine interfacing is the method of surgically removing the scalp and implanting electrodes to record the electrical activity of the brain. Two main technologies dominate the invasive brain machine interface research: ECoG and implanted microelectrode arrays [42]. Electrocorticography (ECoG), is a similar method as electroencephalography (EEG). Instead of recoding electrical activity from scalp, ECoG uses implanted electrodes to record the signals. Electrodes placed under the scalp has a higher spatial resolution than EEG from scalp. Also those signals are less affected by the external and internal artifacts such and EOG, EMG signals and power-line noise. Next method, implanted microelectrode arrays provide higher accuracy signals than ECoG. It is considered as the only BMI technique that allows decoding intended movements of the patient's limb with high accuracy. Even though both ECoG and implanted electrodes provide higher accuracy

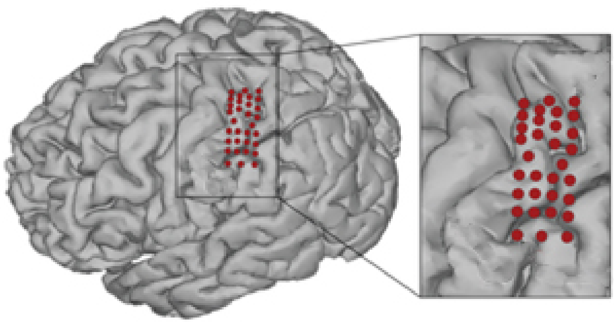


Figure 2.5: Implanted electrodes over the motor cortex

levels than EEG, it is not practical to use those technologies due to invasiveness and higher cost associated. Because of this most of invasive BMI applications are carried out using primates [43–45]. Research carried out by John Hopkins University [46] can be identified as one of the few researches related to human based invasive brain machine interfacing. High density 32 electrode grid was implanted over the left sensorimotor cortex to record motion intentions of the user Fig.2.5. During the experiments participant was able to achieve robust control of a 3D cursor. Invasive BMI research is gaining interests throughout the world and there will be more robust applications in future.

Non-invasive BMI on the otherhand focus of recording electrical activity of the brain from the surface of the scalp (EEG). It's a safe, convenient and relatively inexpensive method that gained interest of researches during recent years. Recent EEG researches such as brain spellers [47, 48] for spell words using brain, brain games [49] for cognitive training, brain controlled hand orthoses [50] and brain controlled wheelchair [51] demonstrate the capabilities of BMI. Fig.2.6 shows the

Figure 2.6: Use of non invasive BMI to control a wheelchair

usage of non invasive BMI during an experiment. Because EEG is recoded on the scalp, signal is subjected to external and internal noise, artifacts which needed to be removed from the final signal to obtain a acceptable signal to noise ratio. As the advancement of machine leaning techniques, signal processing techniques and classification methods now it is possible to obtain more reliable EEG signals from the scalp.

In non inversive brain machine interfaces, six types of signals are being researched [52]. Sensori-motor rhythms (rolandic alpha or mu-rhythms), slow cortical potentials (SCP), event-related potentials (ERPs), steady-state visually or auditory evoked potentials (SSVEP/SSAEP), blood-oxygenation level dependent (BOLD),contrast imaging using functional MRI and concentration changes of oxy/deoxy hemoglobin using functional near-infrared spectroscopy(fNIRS) [52]. MRI and fNIRS need specific equipment that are not accessible in normal research environment. On the other hand, ERPs, Sensori-motor rhythms and SSVEP methods are considered as the most prominent EEG BMI tequniques used in research field.

2.2.5 Event-related potentials (ERPs)

Event-related potentials are the electrical response of the brain to specific events or stimuli [53]. ERPs can be excited by variety of cognitive, motor or sensory events and they provide a non-invasive insight in to psychological states on physiological system responses. ERP signals can be categorized in to two main categories: Sensory signals which occur within the first 100 milliseconds after the stimuli and cognitive signals which are generated in later parts. ERP signal waveforms are analyzed according to the amplitude and latency [53]. Among different ERP methods, P300 is the main research areas under Event Related Potential signals.

P300 is a positive component in EEG signal that peaks 300ms or more after a task-relevant stimulus and oddball paradigm is used to generate the ERP. In oddball paradigm, user is presented with one general stimulus train and one odd stimulus randomly in between the general stimulus. Because human brain focus on the odd stimulus in between the general stimulation, an electrical response can be examined in the brain waves as shown in Fig.2.7. P300 signal depend on number of variables such as the significance of the stimulus, subject's mental state, the task that has to be accomplished, and the degree of attention. [54]. At the earliest stages, p300 signal was used as a lie detector. But currently it is used in many applications such as brain spellers [55], brain controlled wheelchairs [56], games [57] and much more.

2.2.6 Sensorimotor rhythms (SMR)

Sensorimotor rhythms are the rhythmic activity recorded over the sensory motor cortex Fig. 2.8 (a) of the brain. Motor cortex is the region of the brain associated with planning, controlling of voluntary motions in a human body. Sensorimotor rhythms (SMR) are the electrical activity generated by actual movement, motor intention or motor imagery. Frequency range of the SMR waves are from 12Hz to 15Hz for most humans [58]. In SMR based brain machine interfaces, user's imaginary motor moments are decoded and translate them in to control signals. In some researches users were able to achieve both 2D and 3D control of

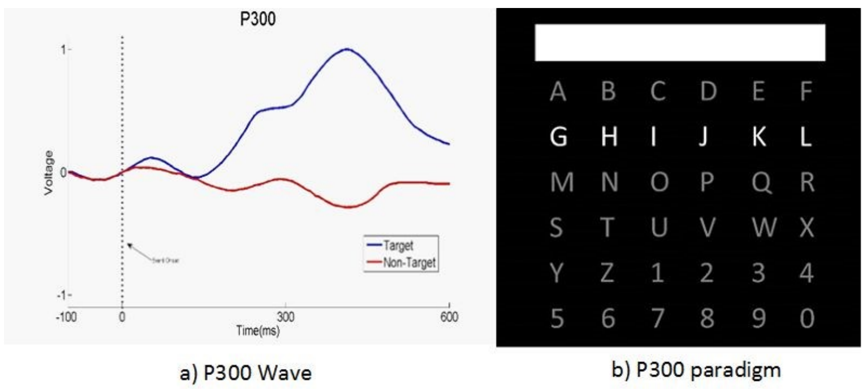


Figure 2.7: P300 wave. Figure from [2]

robots using SMR signals [59, 60]. Research by University of Minnesota evaluate the use of SMR to control a quadcopter in 3D space [60] proving the use of SMR based BMI's potential.

Even though sensorimotor rhythms show promising results in BMI field, few disadvantages limit them from using in online applications. Feature extraction and classification of SMR signals is a complex process when compared with some other BMI methods. This is because SMRs are generated in a small region of the brain and when the signal is recorded from outside, strength of the signal is reduced. Usually brain activity is measured inside the brain in millivolts but from outside of the brain it reduces to micro volts range. Complex filtering and feature extraction methods that have high computational cost must be implemented in order to identify the SMR signals. Also SMR need a longer training time compared with methods such as SSVEP and P300, where user is able to produce the necessary signals without any pre-training. Also accuracy of the SMR classification is relatively low [61] when compared with other BMI methods.

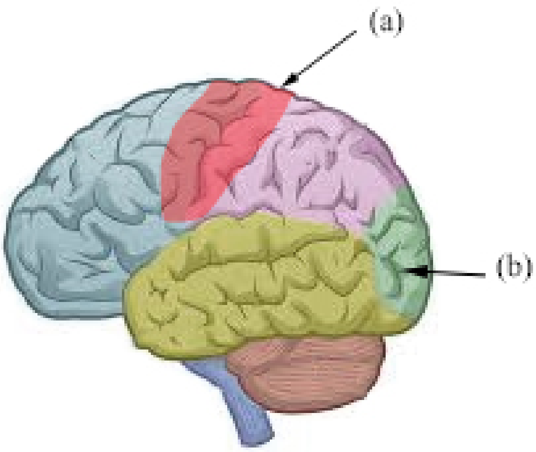


Figure 2.8: (a) Motor cortex. (b) Visual cortex

2.2.7 Steady State Visually Evoked Potential (SSVEP)

Steady state visually evoked potential (SSVEP) is a phenomena created in the visual cortex of the brain (Fig.2.8) (b) due to repetitive stimulations that has different properties such as frequency and phase [62]. Multiple stimuli associated with multiple commands are presented simultaneously to the user to select. User need to focus on the intended stimulus to select the command associated with that stimulus. When the user focus on a target, SSVEP is created as oscillatory signal in the visual cortex of the brain. Focused stimuli evoke SSVEP responses at the corresponding frequency as well as it's harmonics. SSVEP signal can be evoked by flickering visual stimuli in the frequency range of 1Hz to 90Hz [63]. Also SSVEP is evoked in all most all humans making it an another viable control input for users where other control methods might not work [64].

Multiple stimuli based SSVEP being widely used with BMIs for the robustness and high signal to noise ratio of the SSVEP signal. Applications such as wheel chairs [65], home automation units [66] and active prostheses [67] are some of the popular applications based on multiple stimuli based SSVEP. Generally, stimuli are kept at a distance from each other for visual separation. But for subjects who do not have necessary muscle control to redirect the gaze in between stimuli, gaze independent SSVEP BMIs have been proposed [68, 69].

2.2.8 Summary

Controlling of the meal assistance robot can be categorized under two main topics: User input detection and hardware control of the meal assistance robot. In terms of user input detection, most of the existing meal assistance robot use button/ joystick operation as their main input method. Eventhough there are few other control methods such as voice control and eye control, most of them doesn't provide the needed solution for SCI and other patients suffering from severe disabilities. Due to this reason EEG can be identified as a reliable solution which can provide ideal control signal solution for meal assistance robots. Hence, it is important to research on the possibility of incorporating EEG as a control signal. Within EEG, SSVEP can be identified as the best BMI solution due to its high signal to noise ratio and it's possibility to induce in any type of patients who are not suffering brain injuries or coma.

All most all of the existing meal assistance robots use fix point system to feed food to users. But this is not an ideal solution since the user has to be in a fixed location throughout the feeding process. Due to this, it is important to research on adaptive feeding methods which can identify user's mouth location and feed according to that location. Further, in current systems, only method to identify the user's willingness to consume food is by pressing a button or else system will feed at a fixed rate. Other methods to identify user's intention will aid the users with severe disabilities who cannot use current systems.

Chapter 3

OVERVIEW AND HARDWARE DESIGN OF THE PROPOSED MEAL ASSISTANCE ROBOT

3.1 Introduction

Before moving to in-depth details of the proposed system, it is vital to understand the overall working process of the proposed system. Hence, beginning of this chapter will describe the overview of the proposed meal assistance robot. Components and connection of the overall system will be discussed in brief and the control algorithm proposed will also discussed during the overview section. Second section of this chapter will be focused in discussing the design and control structure of the proposed 4DOF meal assistance robot. First, mechanical design and forward/inverse kinematic solutions of the manipulator will be presented along with the hardware components used in fabricating the meal assistance robot. Then, hardware control of the proposed manipulator will be discussed in the later section.

3.2 Overview of the proposed meal assistance robot

The overall system consists of mainly four subsystems: Feeder robot arm, LED panel system, camera system and EEG signal acquisition system. Fig.3.1 gives an overview of the hardware connection of the system. The feeder robot arm is used

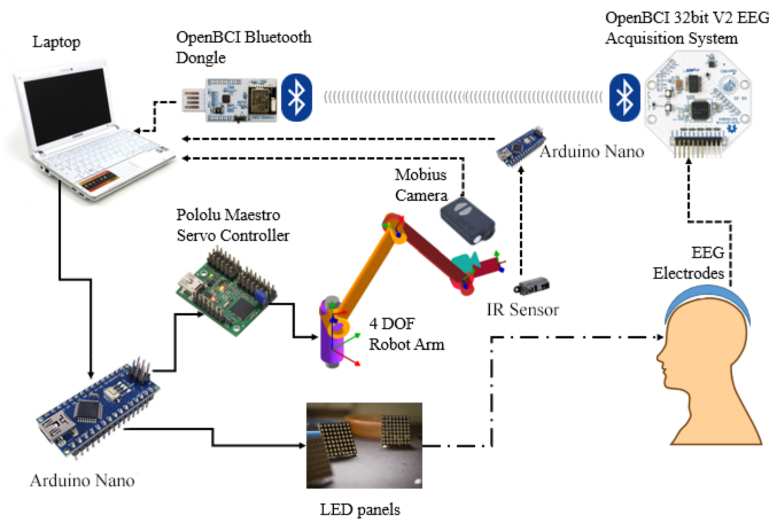


Figure 3.1: Hardware system overview of the meal assistance robot

to perform the feeding motions. It is a RC Servo motors based robot arm which has a 4 Degrees of Freedoms(DOF). RC servo motors are used with an external gearbox to increase the torque while maintaining the smooth motion. Driving of the RC servo motors are realized through a 12 channel servo (Pololu Maestro) controller. High level commands for the servo controller are issued by a laptop where main program is running. Three food containers are fixed on the base frame of the robot arm to store the food items. Adjacent to each food container, an 8*8 LED matrix is mounted and they are used to generate the required visual stimuli signals. An embedded system (Arduino Nano) is used to flicker the LED matrices at 6Hz, 7Hz and 8Hz frequencies.

In order to recognize the user's mouth position and whether it opens or close, a miniature wide angle camera(Mobius) with 1280X720 resolution is used. It is mounted at the end effector above to the spoon as shown in Fig.3.2 . The Camera module is connected directly to the laptop via USB interface. IR based distance sensor capable of measuring distance from 2cm to 15cm was also mounted on the end effector to acquire depth data. Sensor data is transmitted to laptop using an Arduino Nano controller board. Electrical connections will be further discussed in the section 3.3.4. Moreover, to acquire the EEG signals, OpenBCI 32bit V3 8

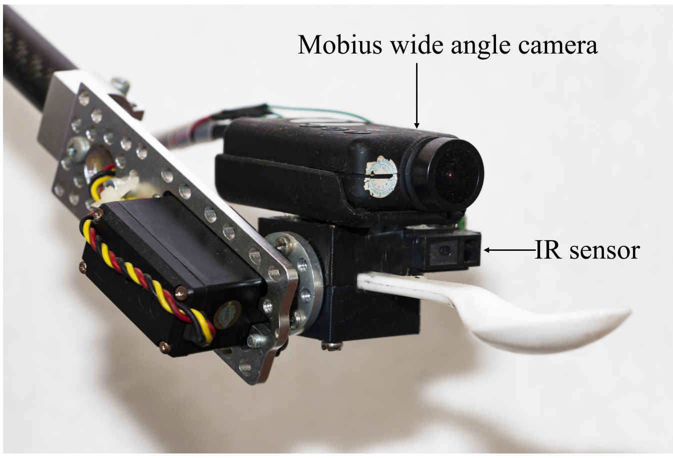


Figure 3.2: Camera mounted of the end effector of the meal assistance robot

channel EEG acquisition system is used. Measured EEG signals at 250 Hz sample rate are transmitted using Bluetooth interface of OpenBCI to the laptop which runs the main program of the system. The laptop (Core i7,12 GB RAM) used in this study is responsible for processing EEG signals, processing camera data and generating servo commands according the implemented program.

Basic control algorithm of the proposed meal assistance robot system is shown in Fig.3.3. At the start of the system, program runs through a loop which used to identify the user intention using SSVEP based classification method. After identifying the user intention, necessary commands will be sent to the feeder robot which will scoop the selected food using a pre-programmed motion path. The spoon at the end effector of the meal assistance robot travels from its rest position as shown in Fig.3.4 (Rest), scoops the food and arrives to a position where the camera can have a wide view towards the user. Since the motion path from the home position to a container and then arrive to the camera tracking position is same for any user irrespective of the situation, for the simplicity, three separate pre-programmed motion paths are implemented for scooping from respective containers. At the end of each motion, the spoon arrives at the same position so that the algorithm could move into automatic mouth position tracking stage.

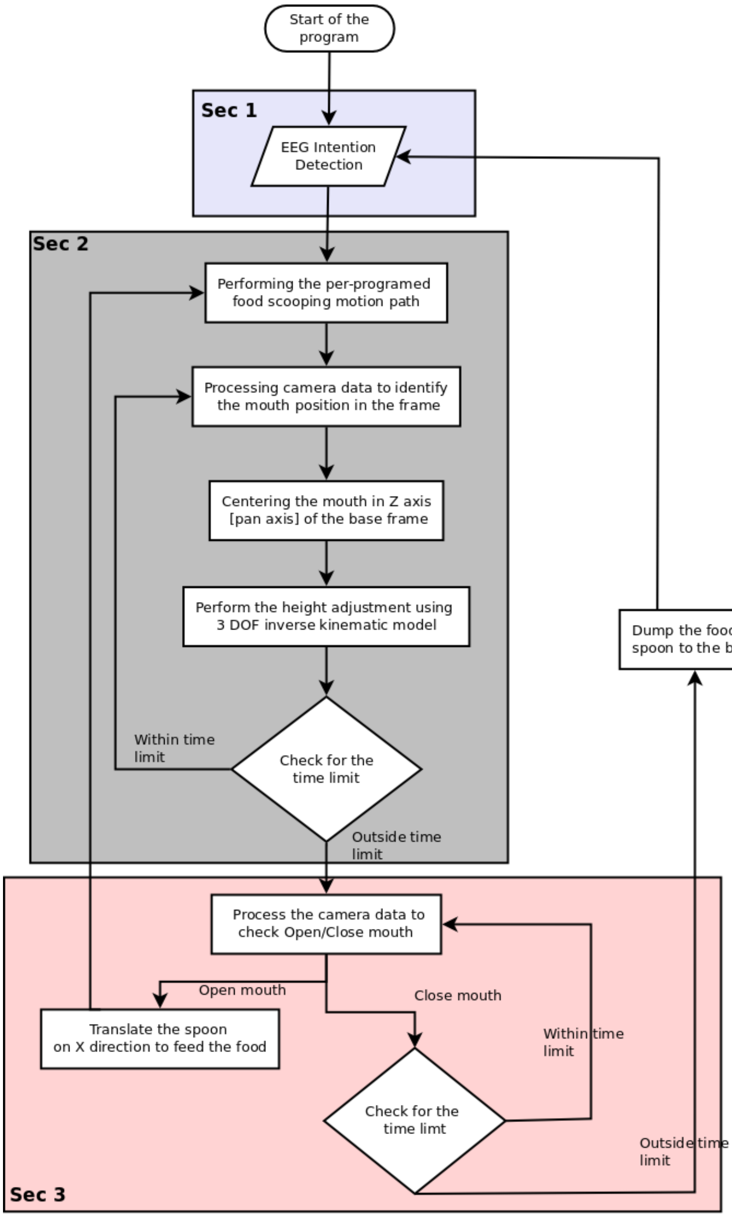


Figure 3.3: Overall control algorithm of the system

Once the robot reaches to the fixed location, the system algorithm moves to the automatic mouth position tracking stage. At this moment, the algorithm starts to track the position of the mouth of the user within the video frame. After positioning the robot according to the user's mouth, algorithm will process the video data to identify the opening of the mouth. Once the user open his/her mouth food will be fed according to the position of the mouth. Identification of the distance that spoon should travel is identified by the IR distance measuring

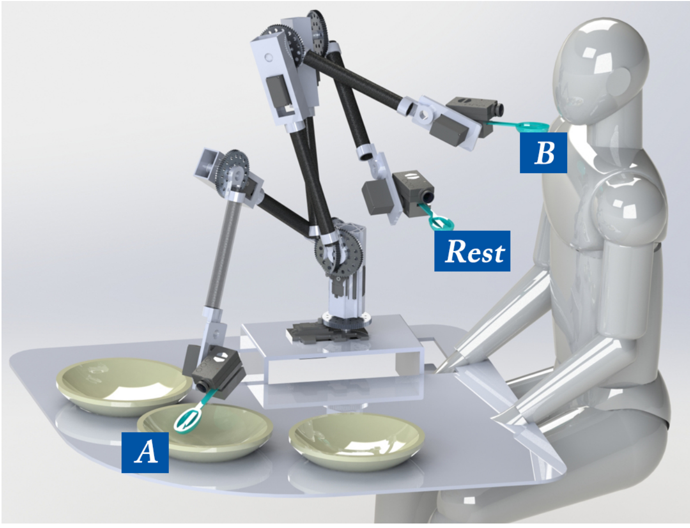


Figure 3.4: **A**: End of scooping motion **Rest**: Initial position of the robot **B**: End of automatic mouth position stage and start of mouth open/closed identification stage.

sensor. After completion of the feeding, robot will continue to feed from the same bowl for a pre-configured time period. Furthermore, feeding bowl selection can be changed using an another user input or stop the feeding process by gazing at the same LED panel that current feeding is carried out.

3.3 Mechanical design and controlling of the 4DOF meal assistance robot

This chapter discusses the mechanical design and controlling of the 4DOF meal assistance robot. Meal assistance robot consists of the 4 DOF robot arm and 3 food containers. Food containers are placed in a quadrant type discussed in the section 2.1.2. Robot arm was designed with the capability ot upgrade in future with end end effector devices such as grippers, camera modules, etc.

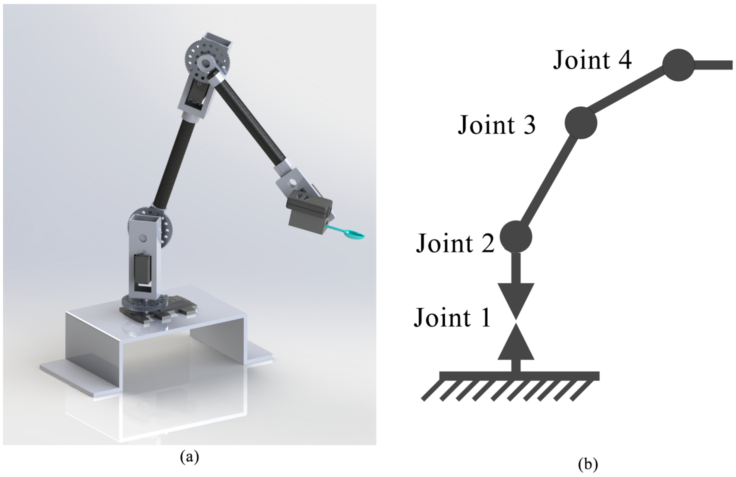


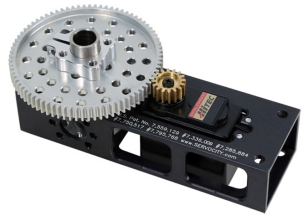
Figure 3.5: (a) 3D design of the meal assistance robot (b) Joint diagram of the robot.

3.3.1 Mechanism and Mechanical Design

3d model of the feeder arm design is shown in Fig.3.5 (a) and the joint arrangement in Fig.3.5.(b) . Modular type design was implemented for future modifications using off the shelve components. Feeder arm consists of two tube mount servo gear boxes [5:1 gear ratio], one top mount servo gear box [7:1 gear ratio], four metal gear servos and various mounting hardware to connect each equipment. Top mount gear box Fig.3.6 (a) with a gear ratio of 7.1 was used for joint 1 which was mounted on an aluminum bracket. Joint 2 and joint 3 comprised of the two tube mount gear boxes Fig.3.6 (b) having 5:1 gear ratio. Each gearbox was connected using 16mm diameter 3mm thickness carbon fiber tubes using 16mm bore 90°clamping mounts [Fig.3.6 (d)]. Spoon and the camera was mounted as the end effector using a 3d printed hardware [Fig.3.6 (e)] and a servo hub [Fig.3.6 (f)] as shown in Fig.3.2. Four Hi-Tech HS-5685MH metal gear servos were selected as the actuation devices of the robot considering the durability and potential future upgrades. Some of the important specification details of the servos are as follows.

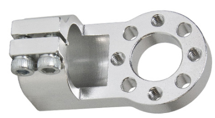
- 6.0V - 7.4V voltage range
- No-load speed (6.0V) of 0.20sec/60°
- No-load speed (7.4V) of 0.17sec/60°

(a)



(b)

(c)



(d)

(e)

(f)

Figure 3.6: (a) Top mount gearbox (b) Tube mount gearbox (c) 16mm carbon fiber tube (d) 90°clamping mount

- Stall torque (6.0V) of 157oz/in. (8.8kg.cm)
- Stall torque (7.4V) of 179oz/in. (12.9kg.cm)
- Max PWM signal range (standard) of 750-2250µsec
- Metal gears
- Operating temperature range of -20°C to +60°C

Fig.3.7 shows the workspace model of the feeder robot modeled using Matlab. Maximum reach along the X, Y, and Z axes are 40 cm, 40 cm and 45 cm respectively. These amounts are sufficient to scoop the food from the designed quadrant type food storage method shown in Fig.2.3. 3 plastic food storage bowls were fixed in an acrylic frame which was used to mount the feeder arm as well.

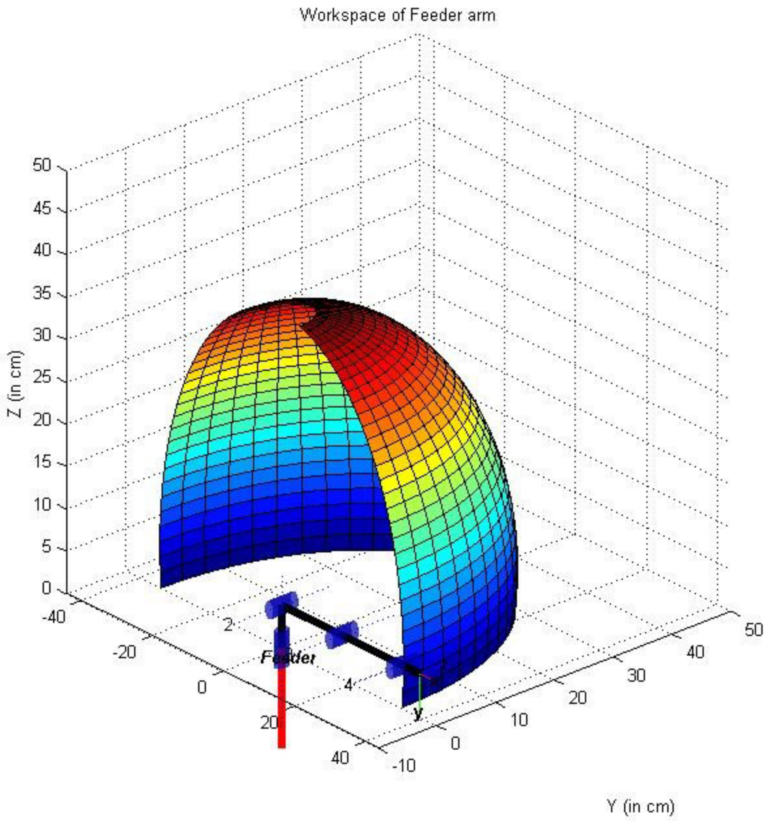


Figure 3.7: Workspace of the designed meal assistance robot

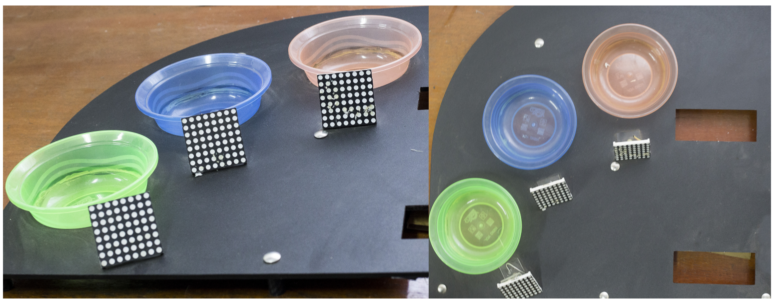


Figure 3.8: Quadrant design of the food storage method.

3.3.2 Kinematic analysis of the meal assistance robot

Analyzing the kinematics of the meal assistance robot is necessary to control the robot in the workspace. Forward kinematic analysis is essential in finding the location and the pose of the end effector using current joint angles. Inverse

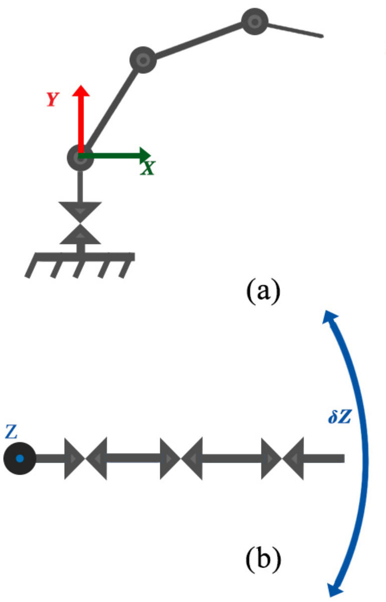


Figure 3.9: (a)3DOF planner robot (b) 1DOF Rotation joint.

kinematics solutions are necessary in identifying the joint angles using the end effector coordinates and pose. Finding forward kinematics of a 4DOF robot arm is possible with different method such as DH parameters, geometrical methods, etc. But solving the inverse kinematics solutions for 4DOF robot using only 3 known parameters is complex and results in multiple solutions. Hence it was decided to simplify the kinematic analysis by separating the robot arm to two kinematic models: 1DOF rotation around the 1st Joint (Fig.3.9 (b)) and 3DOF planner robot arm (Fig.3.9 (a)). Solution for 1DOF rotation joint is straight forward and geometrical solution for 3DOF feeder robot is discussed in the sections below.

Forward kinematics

3DOf feeder robot was defined with the angles and coordinates as mentioned below.

joint angles = $\theta_1, \theta_2, \theta_3$

end effector coordinates = x,y,ϕ

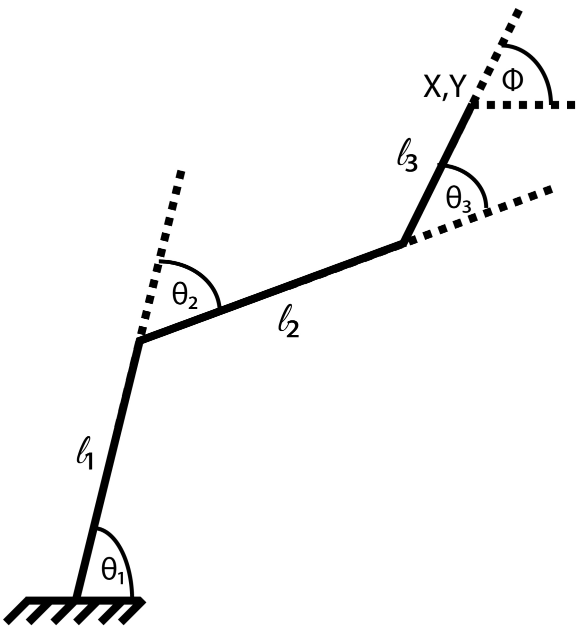


Figure 3.10: 3DOF robot arm for FK

link lengths $= l_1, l_2, l_3$

Position and pose of the end effector can be stated using the equations 4.1, 4.2 and 4.3.

$$x = l_1 \cos\theta_1 + l_2 \cos(\theta_1 + \theta_2) + l_3 \cos(\theta_1 + \theta_2 + \theta_3) \tag{3.1}$$

$$y = l_1 \sin\theta_1 + l_2 \sin(\theta_1 + \theta_2) + l_3 \sin(\theta_1 + \theta_2 + \theta_3) \tag{3.2}$$

$$\phi = \theta_1 + \theta_2 + \theta_3 \tag{3.3}$$

Inverse Kinematics

Reducing the problem to 2DOF manipulator will simply the process of finding solutions. Point on the $3^r d$ joint was defined and P_x, P_y.

$$P_x = X - l_3 \cos\phi \tag{3.4}$$

$$P_x = X - l_3 \sin\phi \tag{3.5}$$

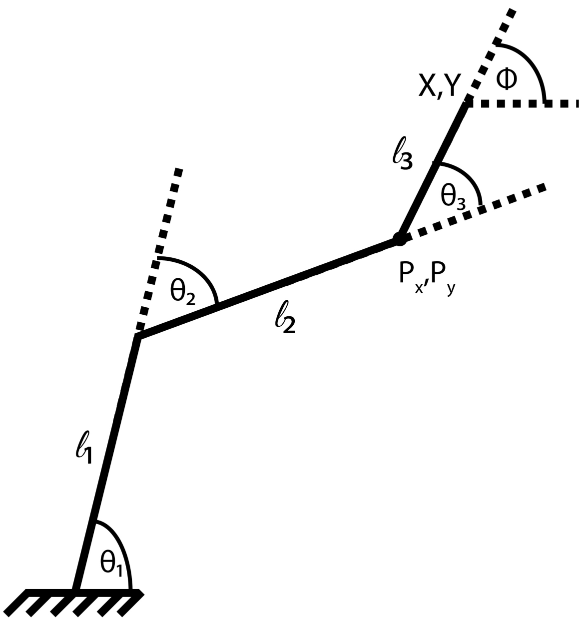


Figure 3.11: 3DOF robot arm for IK

Reduced problem can be graphically represent as in Fig.3.12.

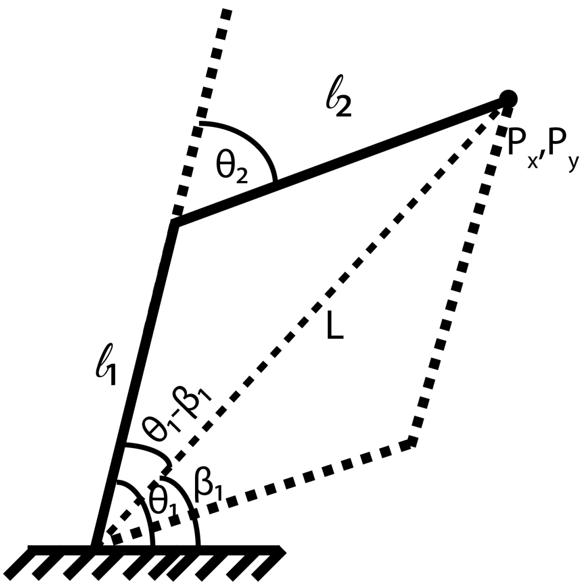


Figure 3.12: 3DOF robot arm reduced to 2DOF solution

$$L = \sqrt{P_x^2 + P_y^2} \tag{3.6}$$

$$\beta_1 = atan(\frac{P_y}{P_x}) \tag{3.7}$$

Applying cos law for the angle $\theta_1 - \beta_1$

$$\cos(\theta_1 - \beta_1) = \frac{l_1^2 + L^2 - l_2^2}{2 l_1 L} \tag{3.8}$$

$$\theta_1 = acos(\frac{l_1^2 + L^2 - l_2^2}{2 l_1 L}) + \beta_1 \tag{3.9}$$

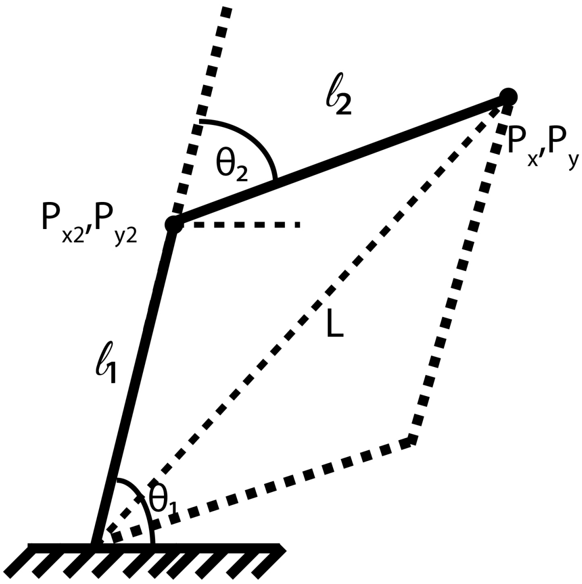


Figure 3.13: 3DOF robot arm reduced to 2DOF solution

Define a point on joint 2 as P_{x2}, P_{y2}. It is possible to represent P_{x2}, P_{y2} from equations

$$P_{x2} = l_1 \cos\theta_1 \tag{3.10}$$

$$P_{y2} = l_1 \sin\theta_1 \tag{3.11}$$

Using the tan representation, $\tan(\theta_2 - \theta_1)$ can be represented as follows.

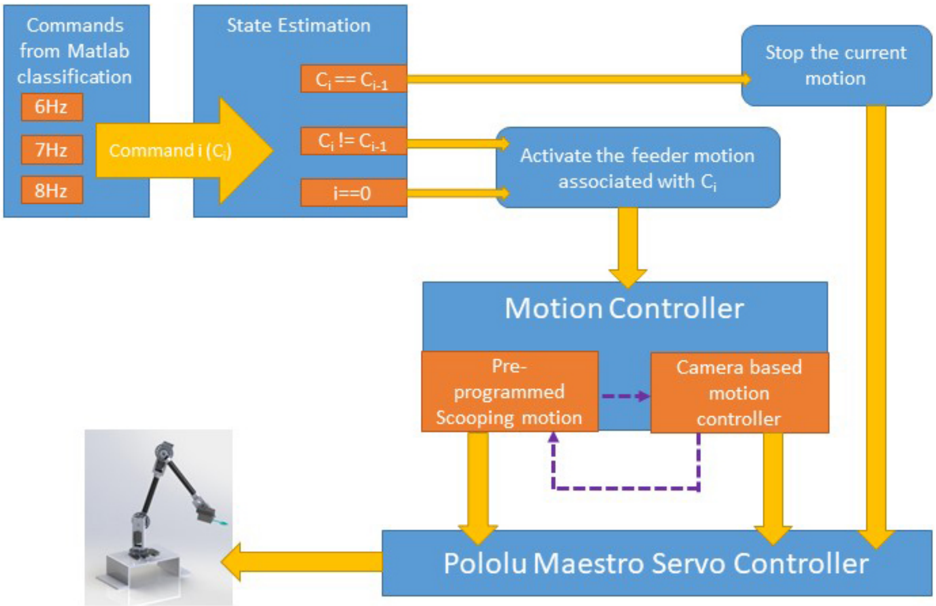


Figure 3.14: Feeder robot control algorithm

$$\tan(\theta_2 - \theta_1) = \frac{P_{y2} - P_{y1}}{P_{x2} - P_{x1}} \tag{3.12}$$

θ_2 can be deduced as

$$\theta_2 = atan(\frac{l_1 \sin\theta_1 + l_3 \sin\phi - y}{l_1 \cos\theta_1 + l_c \cos\phi - x}) + \theta_1 \tag{3.13}$$

θ_3 can be deduced as

$$\theta_3 = \phi - \theta_2 - \theta_1 \tag{3.14}$$

3.3.3 Controlling of the meal assistance robot

Fig.3.14 show the control algorithm used to control the feeder robot. After receiving the classified command from Matlab, feeder arm controller will determine the activation or de-activation of the meal assistance robot using the current status. If it's the beginning of the program it will activate the pre-programed motion path related to the classified signal. If it is not the first control command, it will check for the previous control command. Feeder arm will stop and come to the rest position Fig.3.4 (b) if the current command C_i matches with the previous command C_{i-1}. If current command is different from the previous one, controller will activate the motion path related to new control command.

Each feeding cycle consists of two sub systems: pre-programmed motion path controller for food scooping and vision based motion controller for mouth tracking. Need and application of vision based mouth tracking section controller will be discussed in chapter 5 in detail. Once the controller activates a control command to feed a food from a bowl, first it will perform the pre-programmed food scooping motion. At the end of food scooping, motion path controller will switch to the vision base mouth identification and mouth open/close identification stage. After feeding the food, controller will return to the pre-programmed controller again to scoop the food. This process will continue until the user sends a stop command or 10 repetitions are completed. In case of user's voluntary stop command, food will be dumped again in to the respective bowl and feeder arm will travel in to the rest position.

3.3.4 Electrical component connections

Fig.3.15 shows the hardware connection diagram of the meal assistance robot. Three LED matrices were blinked according to their stimulus frequency using an Arduino Nano controller board. Use of a dedicated controller board is necessary to achieve the correct flickering of the frequency. Four servos were controlled by using a Pololu servo controller board and it was powered via a regulator at 7.4v using an external power source. Controller was connected to the laptop using a USB mini cable and a python script was used to issue control commands. Some of the main features of the controller are listed below. Wide angle camera was also powered using the connected USB mini cable. Furthermore, another Arduino nano was used to acquire the IR sensor data and transfer it to laptop.

Features of Pololu servo controller.

- 12 Channels
- Three control methods: USB, TTL (5V) serial, and internal scripting
- 0.25µs output pulse width resolution
- Pulse rate configurable from 1 to 333 Hz
- Individual speed and acceleration control for each channel
- GPIO pins

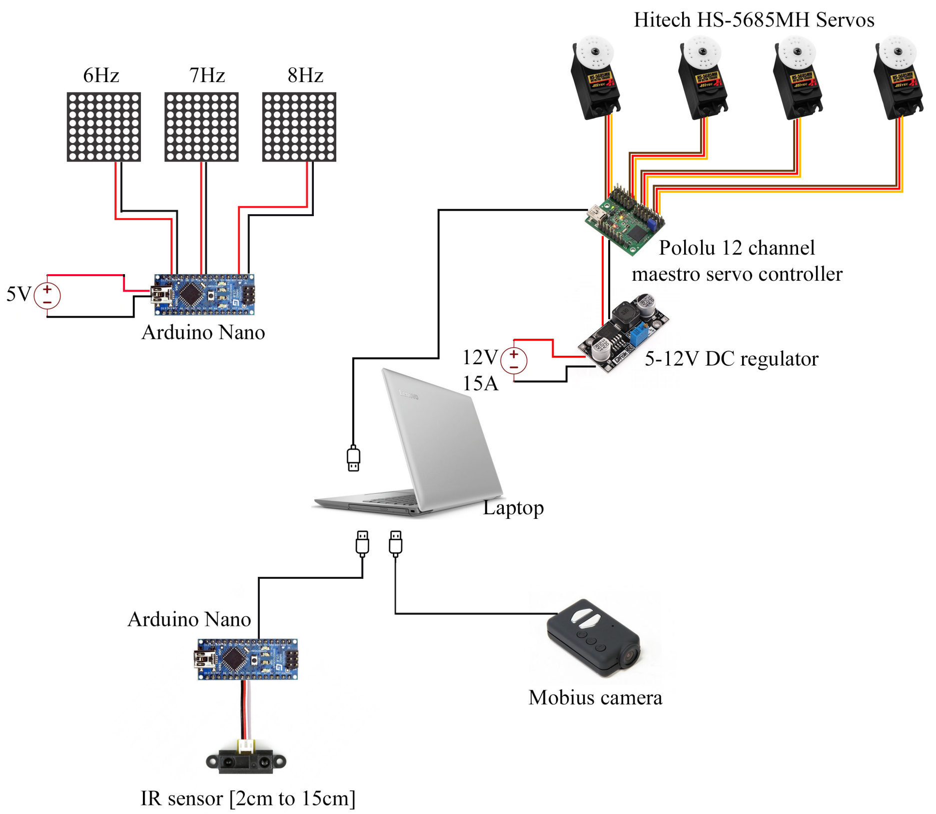


Figure 3.15: Connection diagram of electrical components

Chapter 4

DEVELOPMENT OF USER INTENTION DETECTION METHOD USING EEG:SSVEP BASED BMI

4.1 Introduction

User inputs can be fed in to the meal assistance robot by two main methods. First one as direct control of the robot arm where he/she can direct the spoon to any desired location within the workspace. This need at least six signals to control the robot in 3D space. But this is an impossible goal to achieve using current surface electrode based Brain Machine Interface methods. Second method is to get the input as a selection of food items. In this method user only need to select the food item he/she needs to eat. This is the most common method used in almost all meal assistance robots.

Steady State Visually Evoked Potential BMI can be identified as one the most reliable methods to implement with a meal assistance robot. As discussed in the section 2.2.7, SSVEP is a signal generated in the brain due to external visual stimulations. This can be achieved by flickering a light source at required frequencies. Since three food items were selected for the experiment three stimuli frequencies were needed for the experiment. Furthermore, at the initial stage classification of the SSVEP signal was carried out using Fast Fourier Transformation. But considering the disadvantages, Canonical Correlation Analysis based classification method was implemented at a later stage. This chapter discuss the stage one of the main control algorithm depicted in Fig.4.1

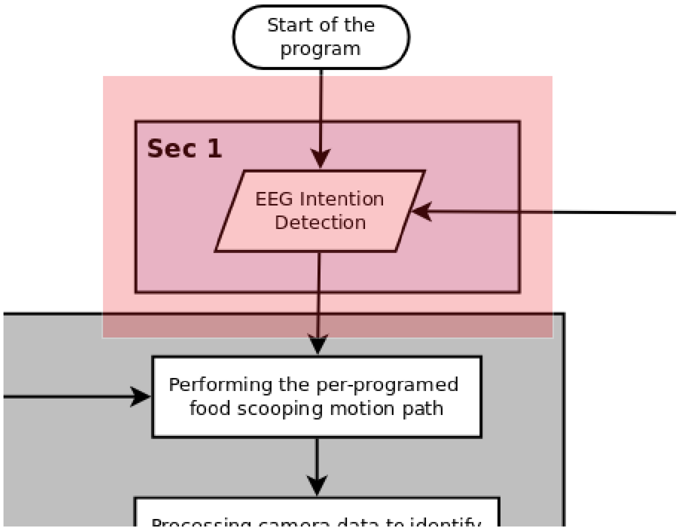


Figure 4.1: Section 1 of the main control algorithm

4.2 Selection of the stimulation frequency

Literature indicate that it is possible to elicit SSVEP signals from 1Hz to 90Hz [63] in human brain. But the signal is considerably prominent in the lower frequency regions. Initially six frequencies from 6Hz to 11Hz at 1Hz intervals was selected for experiments. Initial experiments indicate that there is considerable amplitude from the alpha waves region of the brain wave frequency.

Frequency range from 8Hz to 12Hz is associated with alpha waves which evoked when the user is calm, relaxed and even when daydreaming and inability to focus. Fig.4.2 shows a frequency graph during a trial where two users were not gazing a stimulus. Clear amplitude difference can be seen in the alpha wave range. Due to this frequencies of 6Hz, 7Hz and 8Hz were selected as stimuli frequencies.

4.3 Visual stimuli generation

There are two methods of generating the visual stimuli. First one is using a monitor having a high screen refresh rate (120Hz or higher). Monitor is divided in to different regions and flickered in required frequencies. This is not suitable for the use of meal assistance robot since it cannot be incorporated with the robot effectively. Hence it was decided to use the second method of using a flickering light sources such as LEDs for stimuli generation. Three 6*6, 5mm thick LED matrices were used to generate the three frequencies needed as shown in Fig.4.4.

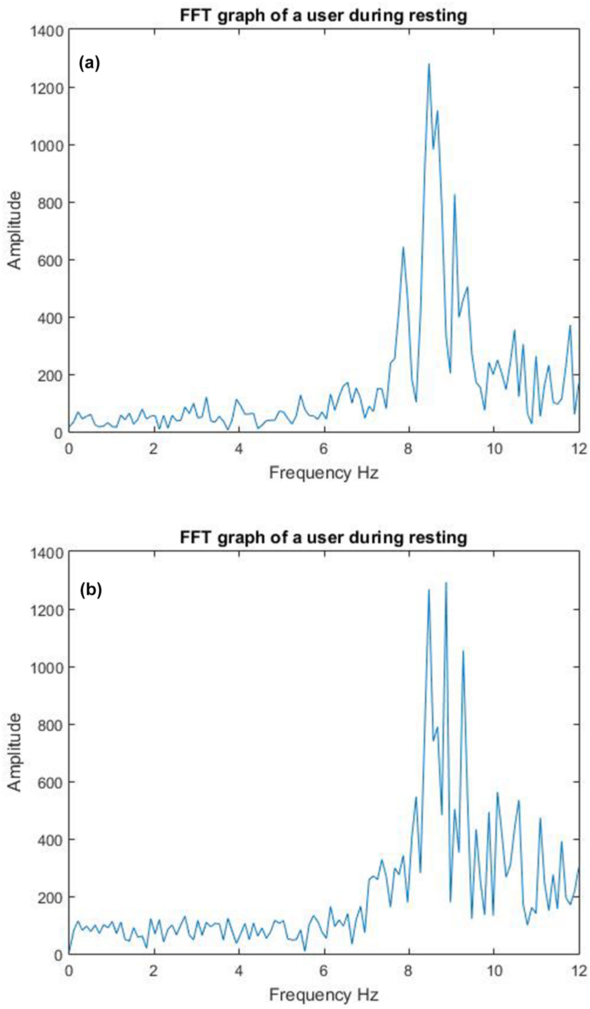


Figure 4.2: (a) Subject A when resting. (b) Subject B when resting

LED panels were fixed 60cm, 70cm and 80cm from the seating position.

Visual fatigue is a common problem in SSVEP BMIs. Intensity of the light source is proportional to the level of visual fatigue. In order to decrease the intensity of the LED panel 250 Ohms Resistor was used in series with each LED panel. Timing of the blinking sequence was precisely controlled using a dedicated Arduino Nano. Fig.4.3 depict the connection diagram of the LED stimuli generation panels.

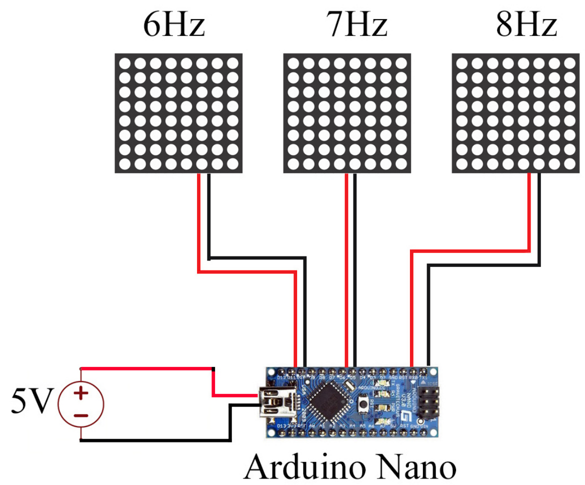


Figure 4.3: LED Panel connection diagram

4.4 Acquisition of EEG signals.

Proper EEG acquisition is essential for the success of BMI systems. Selecting a suitable EEG acquisition system depends on many factors. Number of Channels, Sampling rate, adaptability to the application, cost of the system are some of the major factors that need consideration. Considering above factors it was decided to use the OpenBCI EEG acquisition system for the acquisition process. Specification of the EEG system is given below and the Fig.4.5 shows a photo of the system.

OpenBCI 32bit board:

- 8 differential, high gain, low noise input channels.
- Compatible with active and passive electrodes.
- Texas Instruments ADS1299 ADC.
- PIC32MX250F128B microcontroller w/chipKIT™ bootloader (50MHz).
- RFduino™ Low Power Bluetooth™ radio.
- 24-bit channel data resolution.
- Programmable gain: 1, 2, 4, 6, 8, 12, 24.
- 3.3V digital operating voltage.
- +/-2.5V analog operating voltage.
- 3.3-12V input voltage
- LIS3DH accelerometer.
- Micro SD card slot.
- 5 GPIO pins, 3 of which can be Analog.

OpenBCI daisy module:

- 8 differential, high gain, low noise input channels.
- Compatible with active and passive electrodes.
- Texas Instruments ADS1299 ADC.
- 24-bit channel data resolution.
- Programmable gain: 1, 2, 4, 6, 8, 12, 24.
- 3.3V digital operating voltage.

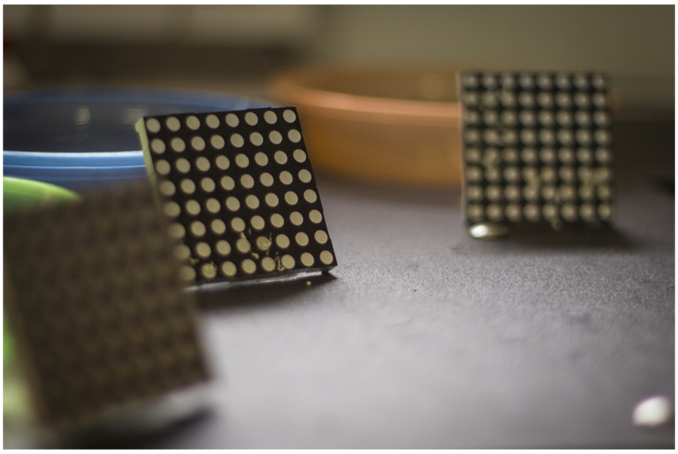
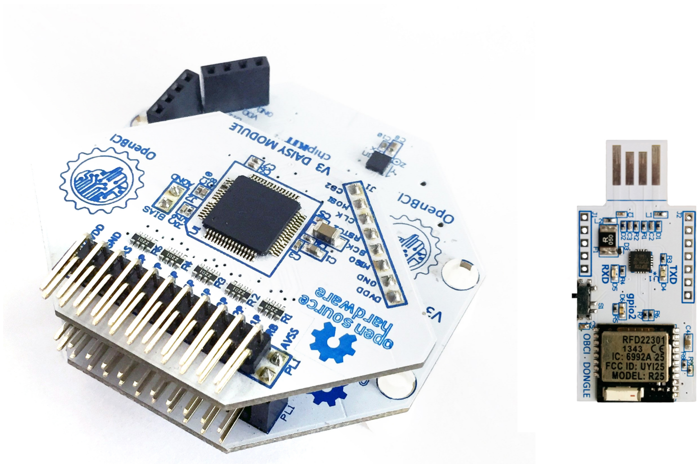


Figure 4.4: 3mm Diameter 8 x 8 LED Matrix



(a) (b)

Figure 4.5: OpenBCI EEG acquisition system

- +/-2.5V analog operating voltage.
- Powered by OpenBCI board

Passive gold cup electrodes

- 26 gauge stranded wire.
- 1-meter, color-coded cable.
- Single female header termination per cable.
- Insulation = PVC rated to 80*C.
- Overall OD = 1.45mm/0.057".

OpenBCI acquisition system is an open source 16 high gain channel, active and passive electrode compatible system capable of transferring data at a 250Hz via Bluetooth. Furthermore, cost of the system is comparatively low with compared to popular EEG systems. OpenBCI system is provided with a Processing™ based GUI which provide basic data visualization capability and a python interface capable of accessing raw data from electrodes.

Out of the sixteen channels, eight was used to acquire the data from the scalp. Gold plated passive electrodes with a conductive paste was used during the experiments. Channels 1 to 8 were placed at the O1, O2, POz, PO3, PO4,

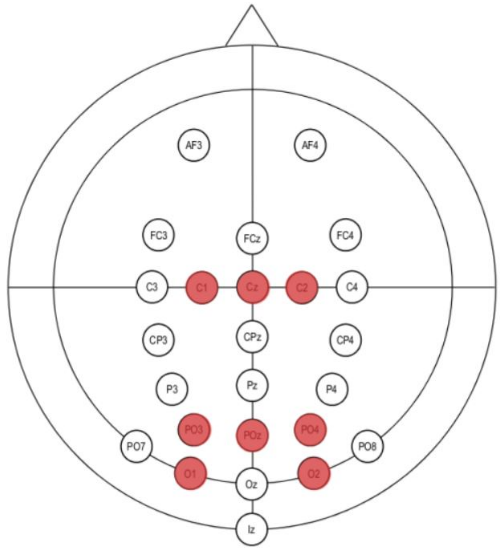


Figure 4.6: Electrode locations used according to 10/10 system

C1, C2, C3 locations respectively according to 10/10 electrode placement system and these locations are shown in Fig.4.6. EasyCap^{TM} electrode placement cap marked with above locations was used in proper placement of electrodes. First EasyCap^{TM} was placed on the subject's head. Sufficient amount of Ten20 paste was applied to electrodes before placing them on above locations. Ten20 paste is used to conduct the signals from skin or scalp to the electrode. Electrodes placed in PO3, POz, PO4, O1, Oz locations are above the visual cortex of user's brain. Visual cortex is the region associated with processing visual data from eyes. Thus it's the area where the required SSVEP signals are been created. Another three electrodes were placed in the locations of C1, Cz, C2. These electrodes act as a reference to indicate the electrical potential on surface of the scalp. Furthermore, reference and ground electrodes of the system were attached to earlobes of the user using Ten20 paste and medical plasters. Electrode paste on a gold cup electrode is depicted in Fig.4.7 and picture of the electrodes attached on the head according to the above described method is shown in Fig.4.8.

EEG system is powered using four AA size batteries and a USB Bluetooth dongle was used to transmit data to the laptop. In the laptop, OpenBCI python

Figure 4.7: Ten20 electrode paste on gold cup electrodes

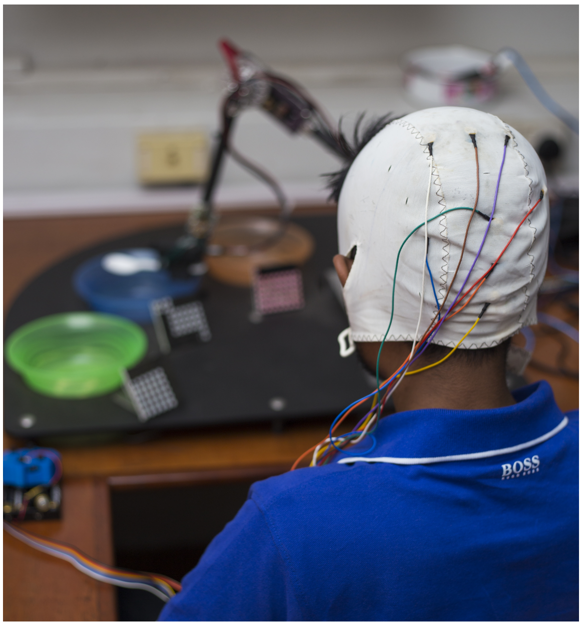


Figure 4.8: Goldcup Electrodes attached to a user's scalp using the EasyCap placement cap

interface along with labstreaming layer was used to transfer data from the dongle to Matlab 2016 application.

4.5 Preprocessing of acquired raw signals

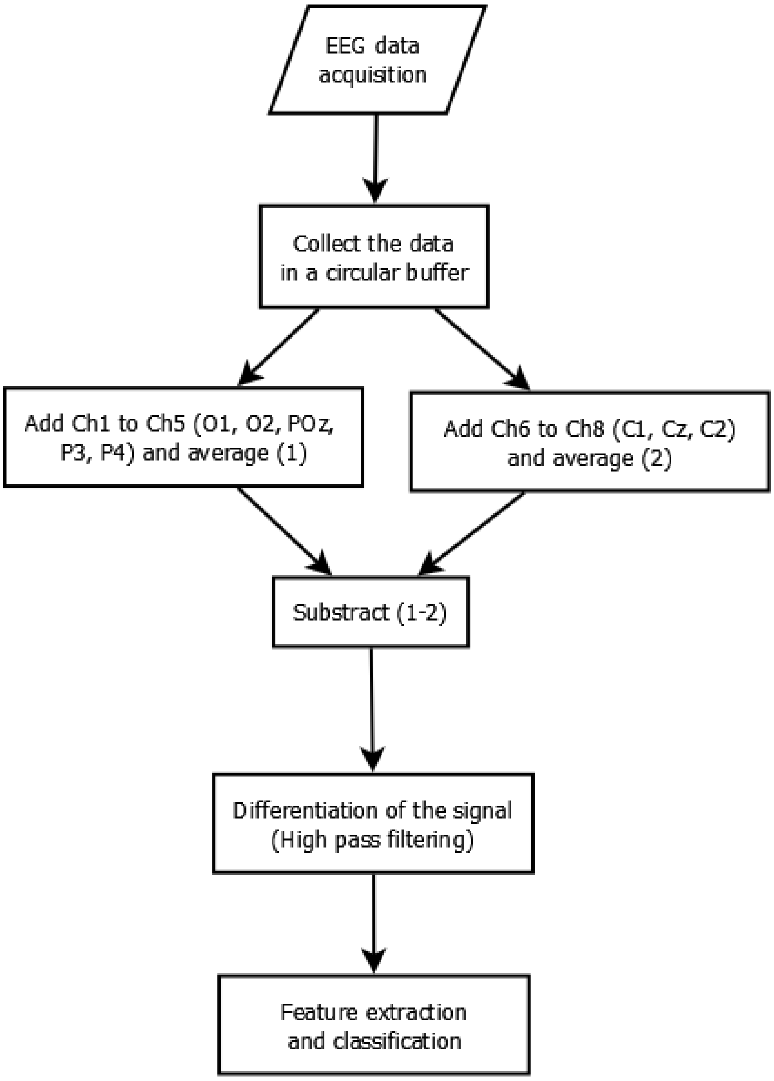


Figure 4.9: Data preprocessing algorithm

Since EEG signals are in micro volts range, many different factors affect the quality of acquired signals. Effect from internal noise, external noise, and artifacts can be reduced or completely eliminated by using preprocessing methods. For the preprocessing and classification process, laptop with a Core i7 processor and a 12 gb memory was used. Fig.4.9 indicate the steps of data preprocessing. First data acquisition was carried out as described using Labstreaminglayer [70].

Labstreaming layer, which used to feed the data to Matlab is an interface to transfer signal data from an acquisition system to different software platforms simultaneously. Matlab 2016b version was used throughout data processing and classification process. In Matlab, two circular buffers having a size of 1000 samples and 2500 samples was used to store the data for CCA based Classification and FFT based classification respectively. Moving Circular buffer having a gap of 50 samples was used as shown in the Fig.4.10. The gap of 50 samples were selected considering the computational power required and the classification speed required. This data window was subjected to the data processing steps shown in Fig.4.9.

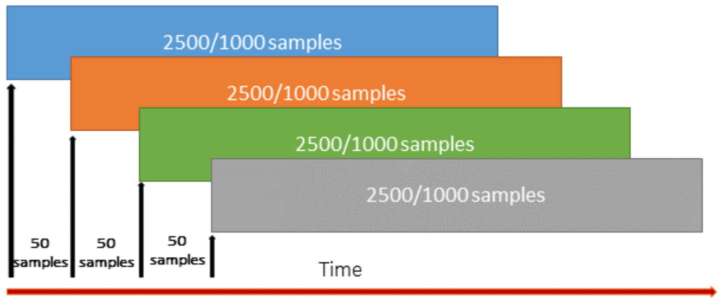


Figure 4.10: Use of Moving window in data processing

First data from 8 channels were separated in to two groups. First group with C1, Cz, C2 and second group with PO3, POz, PO4, O1, Oz electrodes. Two signals were created by adding the channels in each group and averaging them. After that signal from visual cortex region was subtracted by the reference signal. This eliminate the noise and other artifacts common to both electrode sets. Then Matlab was used to differentiate the two signals. This step eliminates the signal drift and keep the signal's base line as zero. Then this pre-processed signal was used for classification. After the FFT implementation, Canonical correlation based classification method was implemented to overcome the disadvantages of FFT based classification.

4.6 Feature extraction and classification of SSVEP signal

Different classification methods can be used to classify SSVEP signals with varying degree of advantages and disadvantages. According to literature, some of the most commonly used classification methods can be listed as follows. Fast Fourier Transformation(FFT), Principle Component Analysis(PCA), Canonical Correlation Analysis(CCA), Multivariate Synchronization Index(MSI). Usage of these methods varies depending on the application. FFT is considered as the primitive method of SSVEP classification. At the initial stage of the research FFT based threshold classification was used to identify the SSVEP signals and control the meal assistance robot.

4.6.1 Fast Fourier Transformation based SSVEP classification

Fast Fourier Transformation is a method of converting time domain signal to frequency domain signals. It creates a set of frequency components using the time

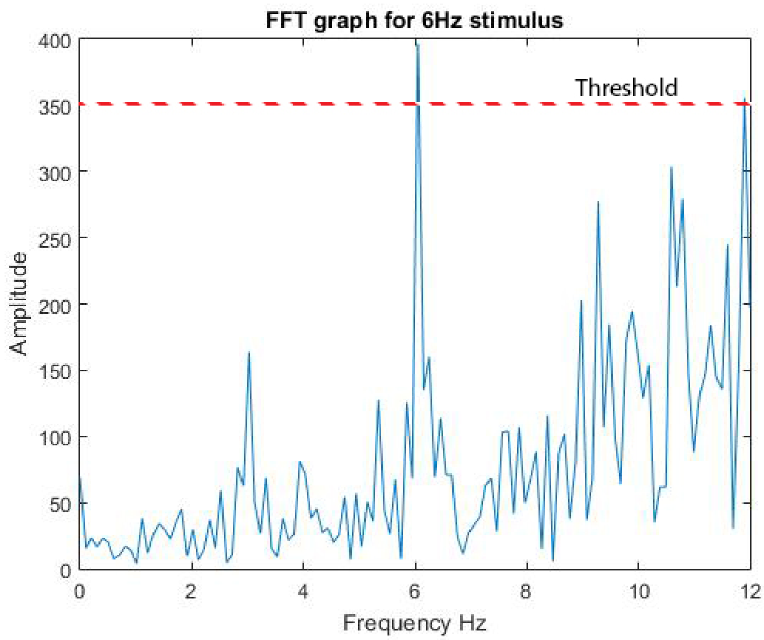


Figure 4.11: 6Hz classification instance

domain signal, each having a distinct frequency with their own amplitude and phase. Amplitude of a frequency will reflect the dominancy of that frequency within the tested signal. This is used to classify the frequency user is gazing. Fig.4.11 shows an instance of a user gazing at LED panels blinking in 6Hz frequency. Classification was done by identifying the frequencies above a threshold as shown in the figure. User specific threshold value was calculated for each frequency in the beginning of the experiment by asking the user to gaze the three LED panels for 60 second each. Furthermore, to generate the required output signals for the meal assistance robot five consecutive classifications from FFT was used. This was to avoid false classifications occurred from signal noise.

Although using FFT is better in terms of computational cost and simplicity, it is not a suitable classification method because of the low accuracy and high average classification time.Furthermore, when threshold classification was implemented, it is important that amplitude from the desired frequencies are considerably higher than the noise level to increase the classification accuracy. Increasing the size of sample window is essential to achieve this. This results in longer classification times undesirable in real-time applications. Canonical Correlation Analysis was selected in order to overcome these problems while increasing accuracy and decreasing classification time.

4.6.2 Canonical correlation based SSVEP classification

Canonical Correlation Analysis is a method of identifying the associations among two sets of variables. Canonical Correlation coefficient is the strength of association between two variables and the goal is to find the maximal correlation coefficient between those two sets. Lin et al [71] first proposed the use of CCA to detect SSVEP signals. CCA method can be described mathematically as follows.

Let X, Y be to multidimensional variables represented as $x = X_t W_x$ and $y = Y_t W_x$. Wx and Wy are weight vectors. Following equation is solved to find the weight vectors, which maximize the correlation between x and y linear combinations.

$$\rho(x,y) = max_{W_x,W_y} \frac{E[xy^T]}{\sqrt{E[xx^T]E[yy^T]}} = max_{W_x,W_y} \frac{E[W_x^T XY^T W_y]}{\sqrt{E[W_x^T XX^T W_x]E[W_y^T YY^T W_y]}} \tag{4.1}$$

When SSVEP classification was carried out using CCA, correlation coefficients between the reference stimuli signal and the EEG signal was calculated and the frequency having the maximum correlation was identified as the classified frequency. For this it is necessary to create a reference signal. The reference signals Y is set as

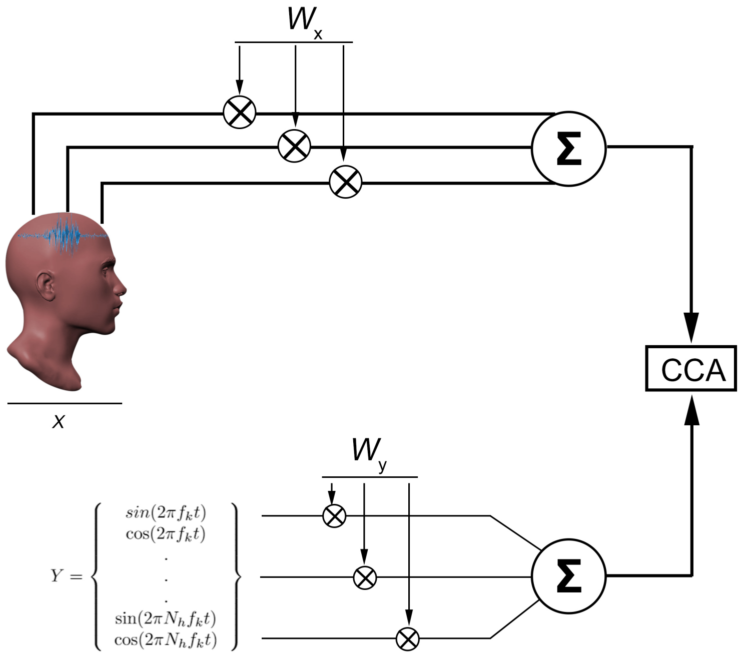


Figure 4.12: Overview of CCA based classification

$$Y = \begin{bmatrix} sin(2\pi f_k t) \\ cos(2\pi f_k t) \\ . \\ . \\ . \\ sin(2\pi N_h f_k t) \\ cos(2\pi N_h f_k t) \end{bmatrix}, t = \frac{1}{F_S}, \frac{2}{F_S} .... \frac{T}{F_s} \tag{4.2}$$

Where f_k is the stimulus frequency, N_h is the number of harmonics, T is the number of sampling points. F_s is the sampling rate. 4 Harmonics (N_h =4) was used in the real time application with a sample size of 1000. Fig.4.12 illustrate the use of CCA when classifying SSVEP signals.

Fig.4.13 shows a instance where the user was asked to gaze at 6Hz, 7Hz and 8Hz LED panels consecutively in 10 seconds intervals. Clear increase in the correlation values can be observed from the correlation graph. At this stage subject was not encourage to adhere a strict time line explaining the delay in

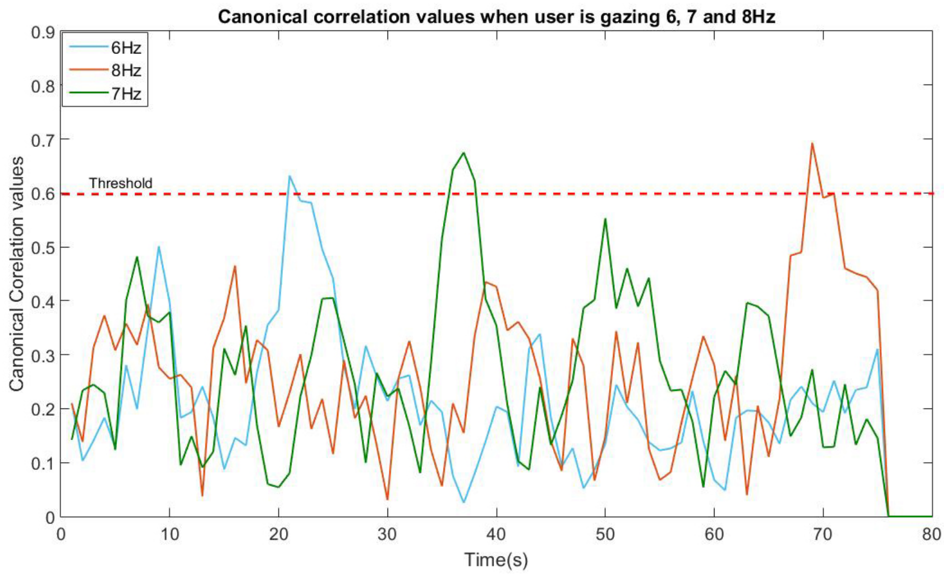


Figure 4.13: CCA correlation values for user gazing.

8Hz peak. During experiments, correlation value of 0.5 was used as the threshold value for classification.

Chapter 5

VISION BASED MOUTH POSITION IDENTIFICATION AND MOUTH OPEN/CLOSE IDENTIFICATION

5.1 Introduction

This chapter of the thesis discusses the use of adaptive vision based feeding algorithm in the meal assistance robot. Specifically, section 2 and 3 of the main control algorithm shown in Fig.5.1. Camera based mouth position identification and mouth open/close identification is an important contribution of this research that intend to solve the issue of fix point feeding and to determine the willingness of the user to consume food. In order to recognize the user's mouth position and whether it is in opens or close condition, a miniature wide angle camera (Mobius) with 1280X720 resolution is used at 15 fps (frames per second).

In the first section of the thesis, automatic mouth position identification and tracking algorithm will be discussed in detail. In the later section, mouth open/close status identification algorithm is discussed in detail.

5.2 Automatic mouth position identification and tracking

Once the food scooping motion path is finished, the system algorithm will move to the automatic mouth position tracking stage. At this moment, the algorithm starts to track the position of the user's mouth within the video frame. In order

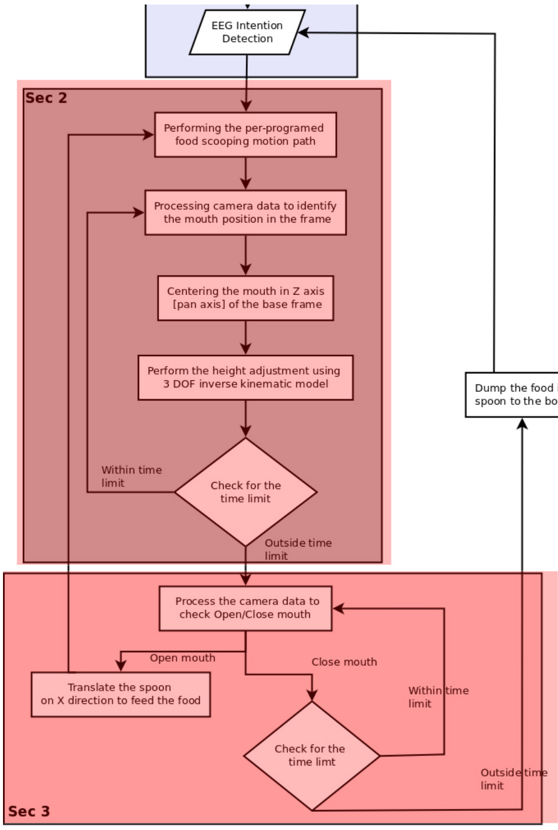


Figure 5.1: Section 2 and 3 of the main control algorithm

to track the mouth, it is necessary to identify the mouth shape in the video frame and to realize this, a Haar Cascade classifier implemented in OpenCV is used. OpenCV Haar classifier is an effective object detection classifier which is used in many applications to do object detection. In order to track the mouth, a pre-trained open source classifier [72] is applied. Furthermore, the classifier is modified to identify the mouths within 10-30 cm distance from the camera. This process omits any mouth shape objects in the background beyond that threshold and allows the program to identify only mouth shapes within the seating area.

When the program identify a mouth position two type of errors can be defined as shown in Fig.5.2 (a). First one is the error in panning direction which is given by δZ. Other error is the height difference between the identified mouth position in the image and the actual height of the user's mouth which is required to feed the mouth correctly. This is indicated in δY. In order to center align the spoon with the mouth position, δZ and δY are corrected during the proposed method.

To generate the motion of the 4DOF robot arm in this stage, two separate kinematic models are used as described in the section 3.3.2. Panning motion around Z axis which is represented by Fig.5 (c) is handled as an independent model. Then, the motions on XY plane (as depicted in Fig.5 (b) is realized as a 3DOF planer robot manipulator separately. When a mouth is identified, the implemented classifier outputs the coordinates of the mouth position as (x1; y1) and the width (w) and height (h) of the bounding box of the mouth. These data are represented in Fig.5.2 (a). Using these data, the error between center of the

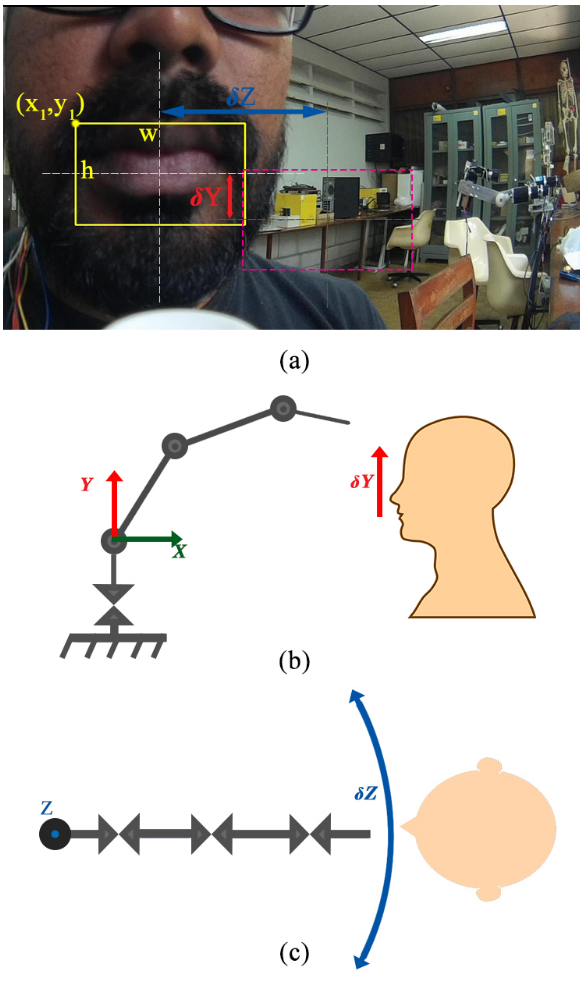


Figure 5.2: Notations and motion directions of meal assistance robot designed in the proposed camera based automatic mouth position tacking method

Algorithm 1: Panning motion (Z direction) adjustment algorithm

if $\delta Z <$ *-50 pixels* **then**
  $Panservo_{new} = Panservo_{old}$ - k;
if $\delta Z >$ *50 pixels* **then**
  $Panservo_{new} = Panservo_{old} +$ k;

identified mouth and the center of the image frame in Z direction is calculated based on following equation.

$$\delta Z = C_x - (x_1 + \frac{w}{2}) \tag{5.1}$$

where the center of the frame given in (Cx; Cy). Then algorithm 1 is used to correct the δZ error by generating servo motor commands of the panning motion motor of the meal assistance robot. In algorithm, the current panning servo position is taken as the $Panservo_{old}$ and k is a constant which sets experimentally. Also the pixel values of -50 to 50 is taken after conducting initials experiments with different values. When the identified mouth center is in between these values it provides the proper centering for the mouth. After correcting the δZ error, the program then corrects the height error, δY as the second step. Correcting δY is carried out considering the robot arm as a 3 DOF planer robot manipulator. At first the error between center of the identified mouth and the center of the image frame in Y direction is derived based on following equation.

$$\delta Y = \frac{C_y}{2} - (y_1 + \frac{h}{2}) \tag{5.2}$$

Then the current position (Ax; Ay) and pose (θ) are calculated using the forward kinematics equations of a 3DOF planer robot. Algorithm 2 is realized whether to increase or decrease the height of the spoon or end effector considering δY. Experimentally it is found out that keeping the identified mouth between -200 to -100 pixels gives the proper height needed to feed the food properly. Inverse kinematics equations of a 3 DOF planer robot are used to calculate the new joint angles according to the output by Algorithm 2. During Z and Y direction align process, Ax is kept at a fix distance from the base frame of the robot arm. k is a constant which is set experimentally.

Algorithm 2: Height (Y direction) adjustment algorithm

if $\delta Y <$ *-200 pixels* **then**
  $A_y = A_y$ - k;
if $\delta Y >$ *-100 pixels* **then**
  $A_y = A_y + $ k;

5.3 User mouth open/close detection

Once the mouth position tracking stage is finished, algorithm moves to the mouth open detection stage. This stage is important since, it provides the user with the facility to accept or reject food at his/her will. Whereas in existing meal assistance robots, it feeds the food irrespective of the user's readiness to eat. In this proposed method, when opening of user's mouth is identified, it gives the program an indication that the user is ready to accept the food.

A separately trained OpenCV Haar cascade classifier is used for distinguishing mouth open from mouth close instances. In order to train the classifier, 430 positive images (open mouth) images and 1300 negative images are used in the training process. Positive samples include the cropped images of open mouth and negative samples consist of full face photos with mouth close. Once the classifier is properly trained it outputs the location of the open mouth if an open mouth is presented in the image. If the classifier detects an open mouth instance of the user, it starts a counter. Once the counter reaches 5 instances of mouth identification, the spoon is set to translate till the distance from mouth to camera is become 8cm. Both no counting instances and distance from mouth to camera was selected using experimental values. Counting 5 instances of mouth identifications aid in removing errors occurred due to false classifications. Depth data was acquired using the IR sensor mounted on the end effector shown in Fig.3.2. After that the spoon holds the extended position for 5 seconds to user to consume the food. Then the spoon pulls back along X direction and start the next feeding cycle. Fig.5.3 demonstrate the user of this algorithm in a normally lit condition.

Figure 5.3: Identification of user mouth open/close status

Chapter 6

EXPERIMENTS, RESULTS AND DISCUSSION.

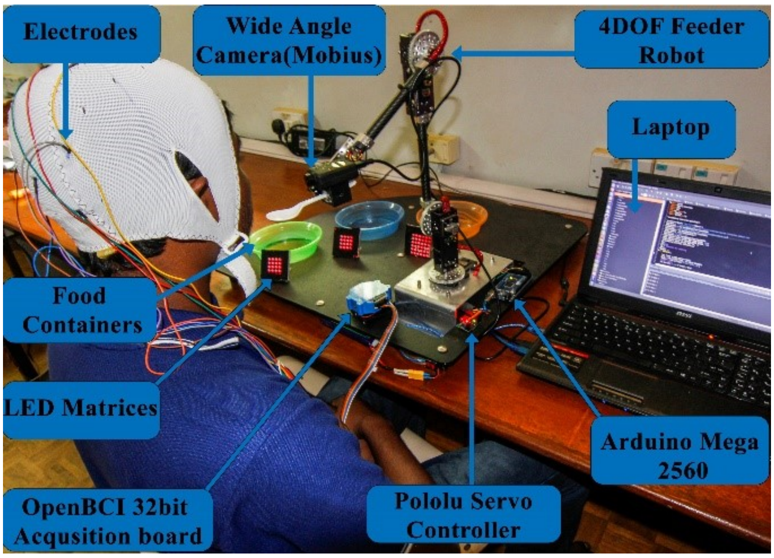


Figure 6.1: Experiment setup

A set of experiments have been carried out to validate the system. Experimental setup used during the experiments is shown in the Fig.6.1. The user was wearing the electrode cap with electrodes attached through the cap. The user was in a seated position in-front of the meal assistance robot (nealr 60cm away) as shown in the Fig.6.1. All the required hardware was connected to the laptop running the EEG classification and visual servoing scripts. Further, Fig.6.2 illustrates the steps diagram of a one feeding cycle. For the illustration purpose food was not included during the depicted experiment.

In order to validate the proposed methods, experiments were conducted under two main categories:SSVEP classification validation and Mouth tracking and

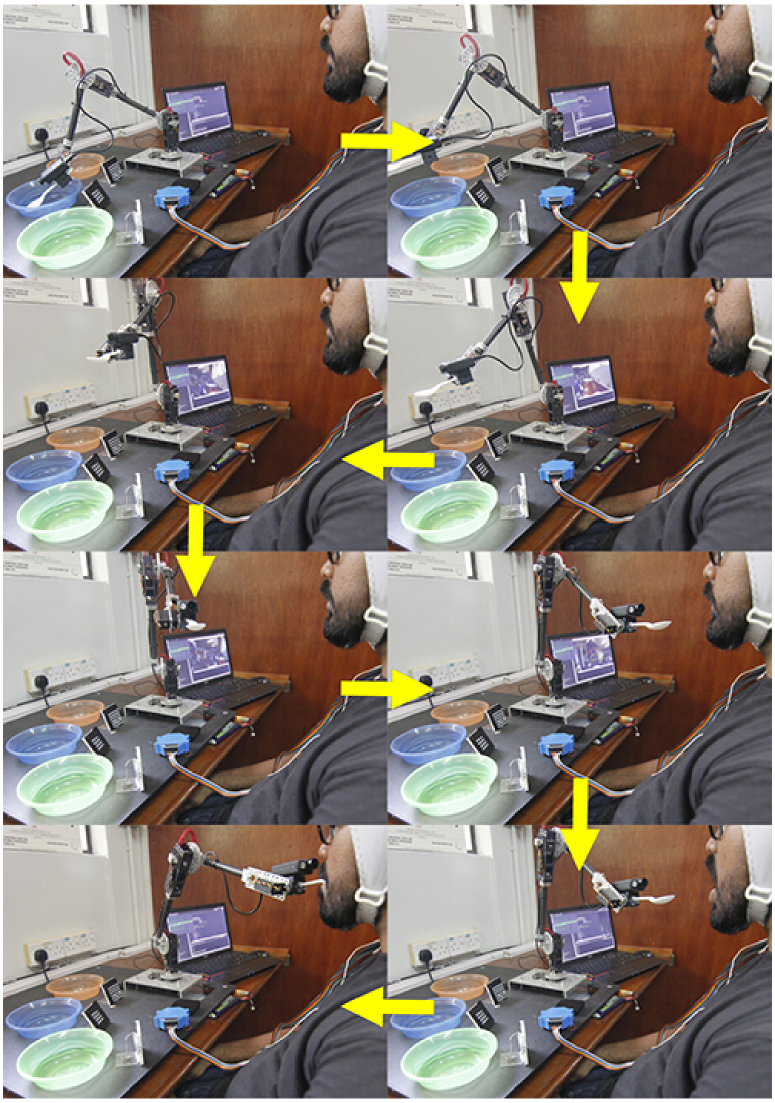
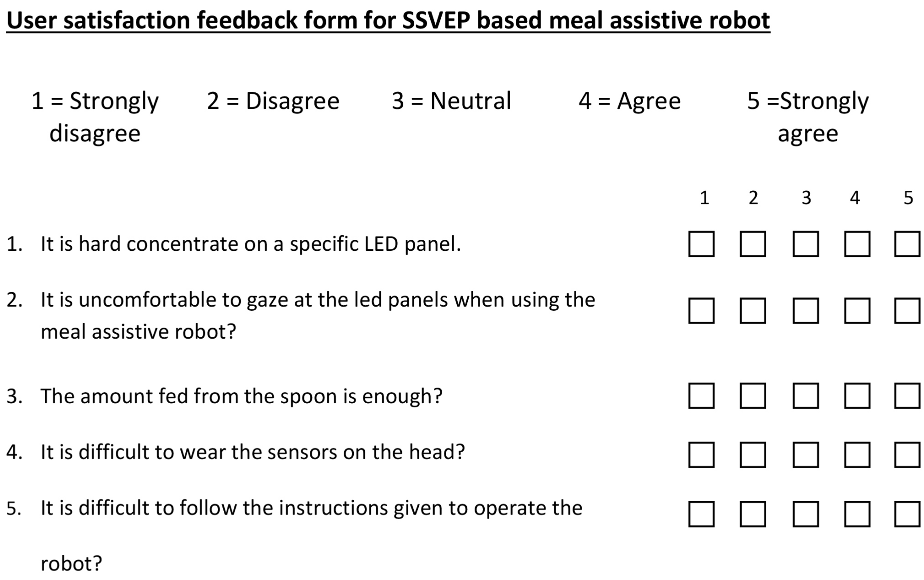


Figure 6.2: Steps followed in one feeding cycle

open/close stage validation. In order to validate the two classification methods five healthy male subjects who were aged 25-28 years participated voluntary for the experiment. All experiments were performed in a typical room lighting level and without outside distractions. During the experiments, subjects were instructed to gaze at the given LED panel in order to select the desired bowl. The time taken from start of this given instruction to start of the feeder arm motion was measured separately for further analysis. This purposed methods deals with gazing at the LED panels and eating from the spoon of the meal assistance robot. Therefor it is important to consider the user feedback about the proposed system and the process. In order to get the user feedback, a questioner was given for every participant at the end of experiment. Given questioner is depicted in FIg.6.3.



User satisfaction feedback form for SSVEP based meal assistive robot

1 = Strongly disagree   2 = Disagree   3 = Neutral   4 = Agree   5 =Strongly agree

	1	2	3	4	5
1. It is hard concentrate on a specific LED panel.	☐	☐	☐	☐	☐
2. It is uncomfortable to gaze at the led panels when using the meal assistive robot?	☐	☐	☐	☐	☐
3. The amount fed from the spoon is enough?	☐	☐	☐	☐	☐
4. It is difficult to wear the sensors on the head?	☐	☐	☐	☐	☐
5. It is difficult to follow the instructions given to operate the robot?	☐	☐	☐	☐	☐

Figure 6.3: Feedback form given to the experiment participants

Fig 6.4 shows the plots of subject D's final FFT signals generated using the algorithm described in Fig.4.9. Significant magnitude difference in relevant fre-

Table 6.1: Accuracy and average classification time using FFT based classification

Subject	Frequency	Accuracy (%)	Average time(s)
	6	85.7	19
A	7	85.7	27
	8	71.4	27
	6	100.0	39
B	7	77.7	39
	8	77.7	39
	6	80.0	22
C	7	100.0	30
	8	90.0	31
	6	100.0	31
D	7	80.0	38
	8	70.0	23
	6	100.0	21
CJ	7	100.0	22
	8	100.0	20

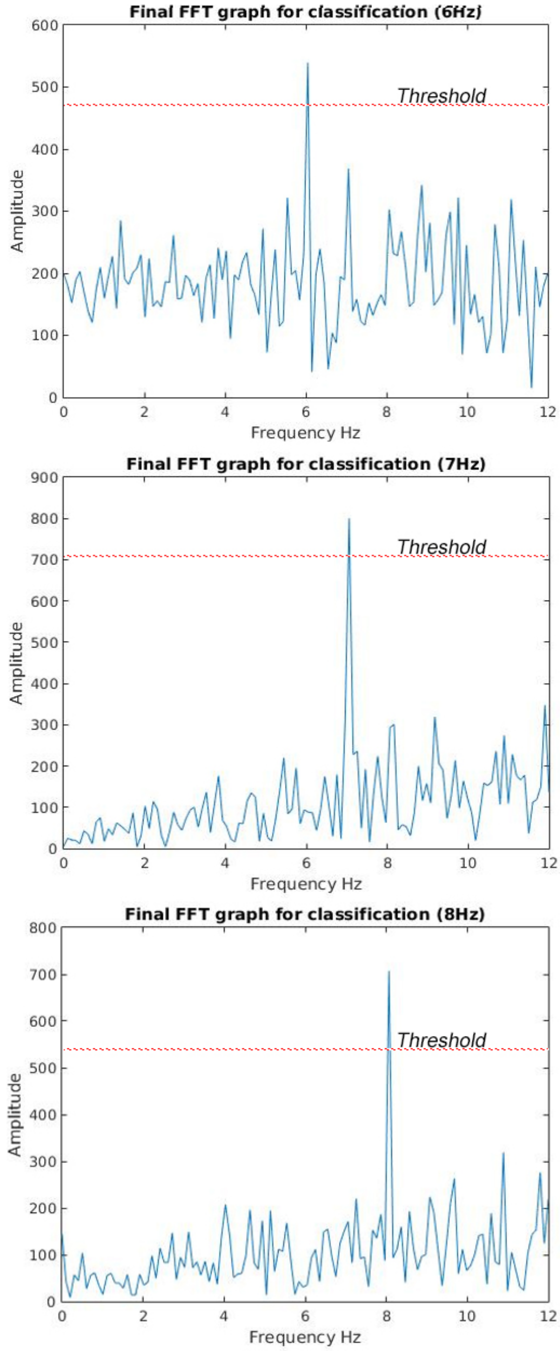


Figure 6.4: FFT plots of 6,7 and 8Hz visual stimulus for the subject CJ

quencies can be identified with compared to noise.

Table 6.1 presents the average classification accuracies of FFT based classifications for all the subjects during experiments. Subjects C and CJ were able to select the bowls with an accuracy more than 80% and classification results of

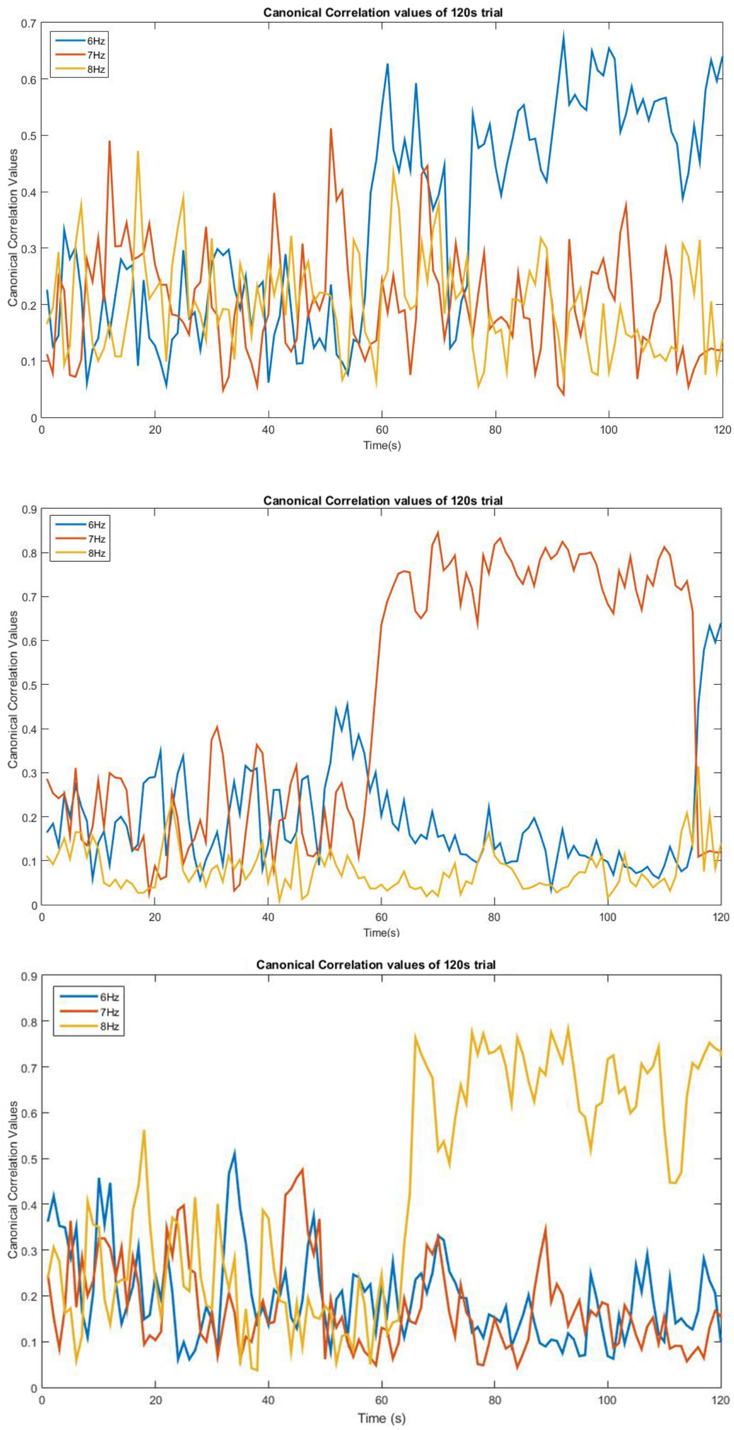


Figure 6.5: Canonical Correlation values of 6, 7 and 8Hz stimuli

other subjects were above the chance level. It should be noted that subject A to D did not have any prior training and only subject E had prior training in SSVEP related experiments. Also Table 6.1 reports the average classification time that took by each subject to correctly command the feeder arm robot. Even though the accuracy levels were above 80% almost every instance, average classification time was above 30s.

Second stage is to verify CCA based classification algorithm. First, in order to demonstrate the change of correlation values, when a user is gazing at a stimuli, one subject was asked to do three trials from 3 frequencies. Fig.6.5 shows the canonical correlation values of subject CJ, when he was asked to gaze at the 3 stimulus. Correlation values were calculated according to the algorithm discussed in the section 4.6.2. Each trial comprise of 60 seconds of rest time and 60 seconds of gaze time. At the start of the trial, the user was asked to rest for 60s and at the end of the 60 seconds user was asked to gaze the 6Hz, 7Hz and 8Hz stimuli. A clear increase of the correlation values can be observed after the subject started to gaze at the stimulus.

Furthermore, another series of experiments were carried out to validate the CCA based classification method. Five male subjects different from the previous set (except subject CJ) was asked to participated in the experiments. Same set of instructions were given and consents were taken before the experiments. Time taken for each classification was recorded for further analysis. Apart from classification time, data needed for the calculation of false positive, false negative and true negative values were recorded. Table 6.2 reports the overview of the classification accuracy and average classification time taken by each subject during the experiments. Figure 6.6 illustrate the confusion plots for each subjects. First 3 elements of the confusion matrix diagonal represents the true positive values of the classifications and forth element represent the true negative classification rate.

Out of the subjects who participated in this second experiments, subject CJ and Q had previous experiences of using SSVEP. As an overview, it is evident that all accuracy values for each subjects at each frequency values are above the chance

Table 6.2: Accuracy and average classification time using CCA based classification

Subject	Frequency	Accuracy (%)	Average time(s)
	6	86.7	9.6
CJ	7	93.3	9
	8	93.3	9.3
	6	80.0	9.5
Q	7	90.0	10.0
	8	95.0	8.8
	6	85.7	11.0
R	7	92.9	8.4
	8	89.3	11.3
	6	60.0	11.6
S	7	76.0	9.9
	8	88.0	6.9
	6	86.7	11.9
T	7	93.3	6.2
	8	90.0	7.1

level. Additionally, around 10% of false positive classifications can be observed from all most every experiment subject at every frequency. Subject Q display the least false positive classification rate as an average and subject S display the highest amount of false classification rate. Also Subject S's classification of 6Hz frequency is account for the lowest amount in classification accuracies(60%). Highest accuracy of the set can be observed from the subject Q's 8Hz classification results (95%). Subjects who had previous experience with SSVEP had a low level of false classification and high level of true negative classifications. Particularly, their false classifications during the rest period was comparatively low. Moreover, false classifications caused by 6Hz frequency is at the minimum. For most of the subjects it was at the 0% rate. But subject R and T displays a small amount of false classifications of 6Hz at 3.6% and 3.3% respectively.

Figure 6.7 represent the overview of the classification time data distribution (mean, 25th and 75th percentiles, most extreme data points and outliers). Also figure 6.8 illustrate the mean classification times and standard deviations of the classification time taken by each subject. Results show that average time taken for the classification of each frequency is around 10 seconds. Lowest classification time recorded in the data is 3 seconds. Moreover, there were outliers for the subjects Q, S and T which exceeded 25 seconds.

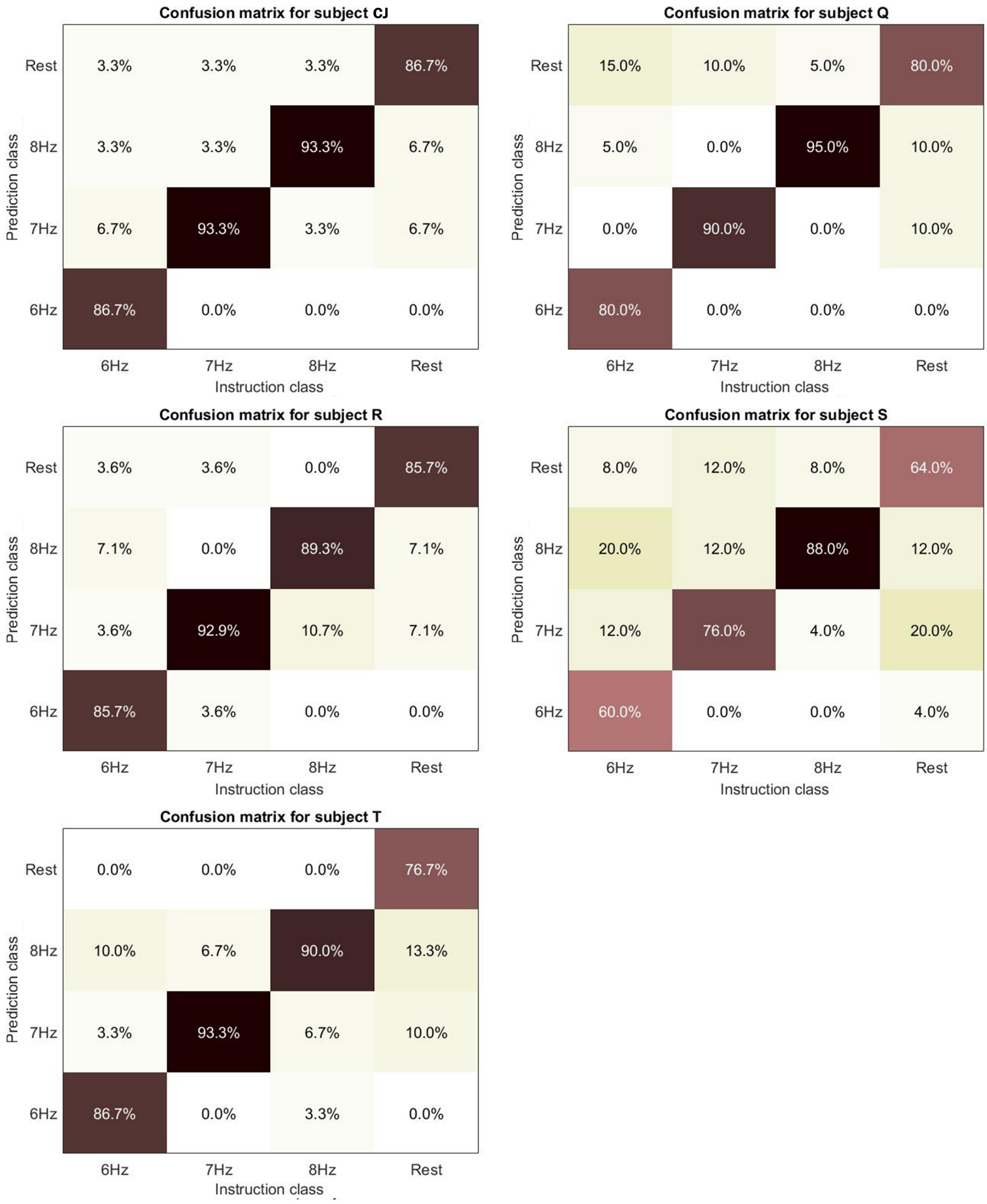


Figure 6.6: Confusion matrices for each subject.

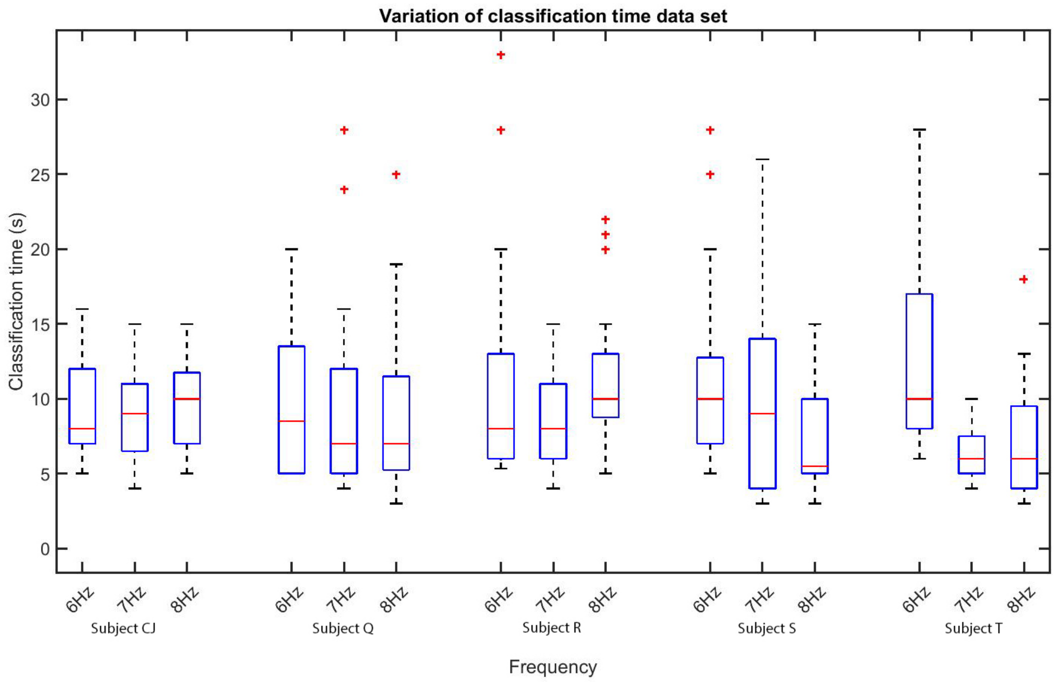


Figure 6.7: Average classification times for each subject at each frequency

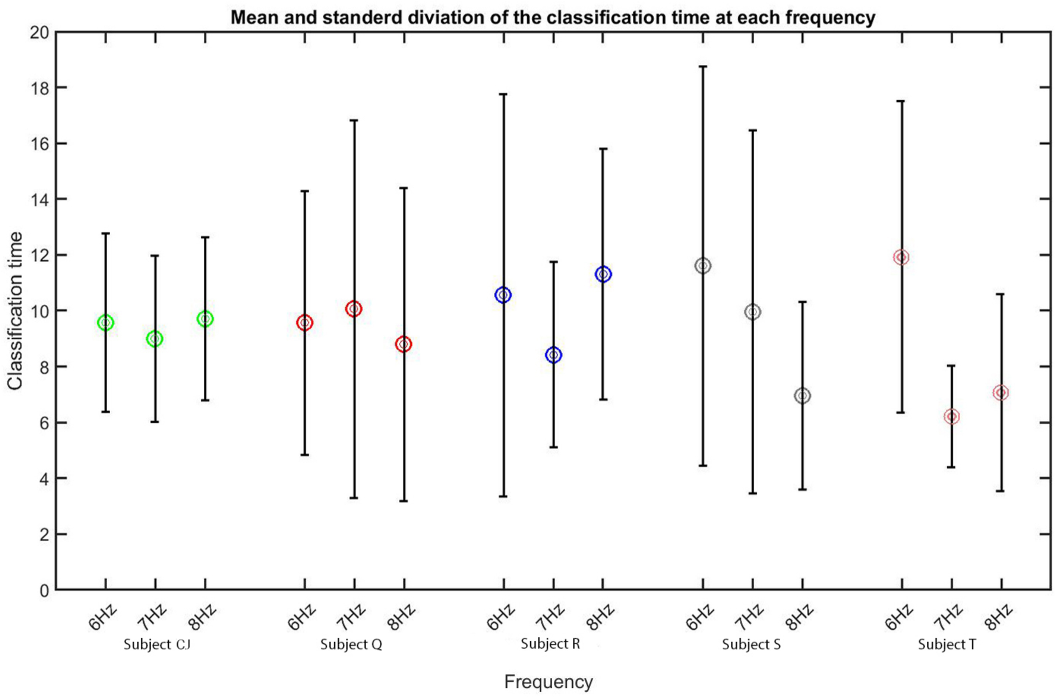


Figure 6.8: Mean and standard deviation of the classification time taken by each subject

In order to validate the automatic mouth position tracking and open/close identification, the algorithm was executed only for each stage and analyzed the results. Six subjects were participated voluntarily in the experiments. Sample image sequence of the motion of spoon which was captured using end-effector mounted camera from the fixed position at the beginning of the stage to correctly centering along mouth at the end is shown in Fig.6.9.(a). For all the subjects, the proposed tracking method was able to effectively track the mouth position during all the trials. Time taken to correctly track the mouth and center is recorded and Table 6.3 summarizes the results for all the subjects. It can be seen that the proposed method was able to track the mouth position of any user with an average time below 12 seconds. Also Table 6.3 presents the accuracy rates of open mouth detection , average time taken to recognize the open mouth and the standard deviations. Fig.6.9.(b) present the instances of mouth open detection performed on 3 subjects. First raw illustrate the user at resting position and second raw illustrate the identification of the mouth open, represented by the green box.

Table 6.3: Performance of the camera based mouth position tracking method and mouth open/close detection method

Subject	Time taken to track the center of the mouth (s)		Mouth open detection accuracy	Time to identify mouth opening(s)	
	mean	SD		mean	SD
CJ	9.3	0.3	100	0.8	0.1
L	10.2	0.2	100	1.8	0.6
M	11.1	0.9	100	3.7	1.1
N	10.1	0.4	100	2.7	1.6
O	10.2	0.2	100	1.8	1.1
P	10.0	0.2	100	0.1	0.1

Fig.6.10 depict the scores of the feedback form given for users. First question was asked regarding the ability to concentrate on the LED panels. Averagely, users indicated that they are it is not hard nor easy to concentrate on the led panels (average score of 2.9). Second question was asked on the comfortability of the eye when gazing at the LED panels and averagely participants agreed that it was difficult to gaze at the LED panels (average score of 3.9). According to

the answers form the 3rd question, users agreed that the food amount scooped is enough for biting (average score of 4). Further, answers from question 4 indicate that users agree to the statement of "it is difficult to wear the electrodes on the head" (average score of 3.7). Answers form the final question reveal that users disagree (average score of 1.9) to the statement of "it is difficult to follow the instructions".

Figure 6.9: (a) Image sequence of mouth position tracking process as seen from the end effector mounted camera. Yellow colored box represents the detected mouth shape by the algorithm (Subject P) (b) Detection results indicating open mouth status of subject L, M, N. Green colored box indicates the detected mouth open status by the algorithm

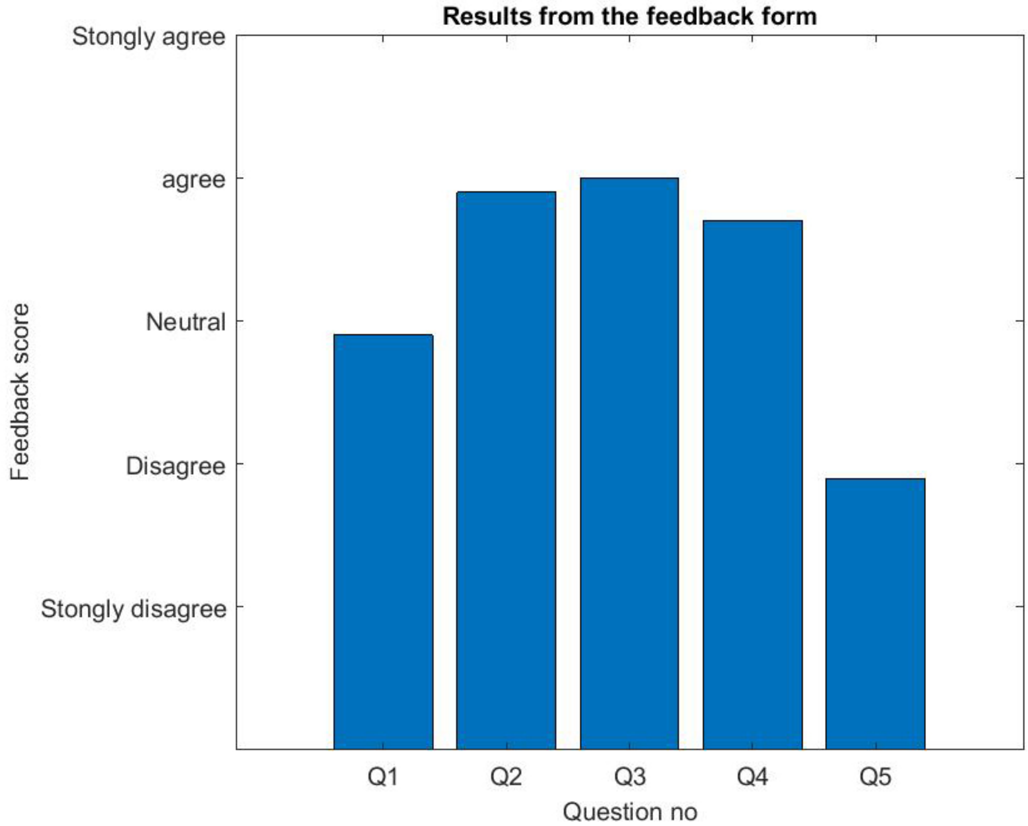


Figure 6.10: Results from the feedback form

6.1 Discussion

Self-feeding is one of the main Activities of Daily Living performed by a human in his/her life time. However, people who suffer from disabilities such as spinal cord injuries, upper limb dis-articulations, paralysis will not have the opportunity to feed themselves. They will either need the assistance from a care taker or they will have to use specially designed meal assistive devices to feed themselves. Meal assistance robots are one of those solutions designed to cater the need of disabled individuals in intaking their food.

It is possible to find different types of meal assistance robots as both commercial products and research designs. One major drawback identified during the literature review process was the limitation of control methods used. Most of the robots used button/joystick as their main control input and it limit the user group significantly. There are few innovative control methods such as eye tracking, sip and puff switches and voice recognition that have tried to address this issue. But it is important to research on other possible control solutions that can increase the device's user group. In additionally, it was identified that another important drawback in current meal assistive devices was the feeding method. All most all the systems use a fix point to feed the food and user had to preadjust this fix point to consume food at the correct location. Once configured he/she had to stay at that point without moving the location of the head to intake food. Furthermore, food was fed at a continuous rate without considering the willingness or readiness of the user to consume food (Unless there is a separate control input to indicate the willingness of the user). Based on these research problems, this thesis proposed an EEG signal based Brain Machine Interface for a meal assistance robot which is capable to adapt the feeding location according to the user's mouth position and which is able to identify the user's readiness to intake food (Mouth open of the user).

In this research, 4DOF robot with a spoon as the end effector was designed and fabricated to act as the meal assistance robot. A geometry based kinematic analysis was conducted to solve the system's forward and inverse kinematic solutions. Additionally, a wide angle camera was mounted on the end effector to get image data necessary in adaptive feeding system and user's mouth open detection system. For both mouth tracking system and mouth open detection system, OpenCV based algorithm was constructed and validated using six subjects. Further, SSVEP based Brain Machine Interface was designed to identify the user's food selection. 3 LED stimuli flickering at 3 different frequencies (6Hz, 7Hz and 8Hz) was used to designate 3 food containers. Then two classification methods were tested with 5 healthy subjects to validate the proposed system.

Finding from this research validate the successful use of the brain machine interface for the meal assistance robot. Users were able to successfully control the meal assistance robot using the SSVEP based Brain Machine Interface. Using the Fast Fourier Transformation based classification method, it was possible to attain high accuracy levels. But time taken for classification was high, resulted in eye strains of the user after few minuets of use. On the other hand, using the classification method Canonical Correlation Analysis, it was possible to achieve high classification results with shorter classification times with compared to FFT based classification. Average classification time of 28.5s could be reduced to 9.3s using CCA. It is a considerable decrease in the classification time without compromising the accuracy levels. However, few outliers were present in the data which took more than 25 seconds to classify the output. In term's of the accuracy, CCA based classification resulted in high accuracy rates above 80% for most of the subjects.

All subjects except S, displayed accuracy levels above 80%. But only the subject P was able to produce false classification rates below 10% for all frequencies. However, subject R and T, each had only one instance of false classification rate above 10%. Subject S however demonstrated a relatively low classification rate when he was instructed to gaze at 6Hz LED panel. Similarly 46% of the resting state of subject S was classified as false positive outputs from the algorithm. It may be required to identify different frequencies for subject S to increase the accuracy levels.

It was evident from the results that, subjects who had previous experiences of SSVEP based BCI illustrate high level of true positive classification accuracies while maintaining high level of true negative classification rates suggesting that with experience users can increase the classification accuracies and decrease false classification rate.

Furthermore, satisfaction survey reveal that users reported discomfort when wearing the EEG electrodes for a long period of time during experiments. This is due to the gel type electrodes that are being used in experiments. The adhesive Ten20 gel used in experiment is a high viscous gel, but after some time it's viscosity get reduced due to body heat and sweat, making the user uncomfortable of wearing the electrodes. Additionally, reducing the no of electrodes will also increase the user comfort. Investigating the possibility of reducing the electrodes without decreasing the accuracy will be paramount in future studies. Another important fact revealed by the survey was the uncomfortably in gazing at the LED panels. This is a common disadvantage occur in SSVEP. Scientists are researching on finding solutions to minimize the effect from the flickering LEDs. Reducing the surface area of the LED panel and reducing the intensity will aid to increase the user comfort.

Mouth tracking and open state identifying methods were more than adequate for the task. Both systems were able to track and identify the mouth open condition in every experiment. Average time to track the mouth was around 10s and average time to identify the mouth open was around 2 seconds. But it was observed that two methods were dependent on the lighting level of the environment. Both methods underperformed in dark environments or backlit environments. Exposure compensation measures can be incorporated to the image processing algorithm to increase accuracy in such conditions.

Chapter 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

In this thesis, a meal assistance robot with an EEG based brain machine interface was proposed and the system was validated using experiments. First stage of the research was to design and fabricate a 4DOF meal assistance robot capable of handling multiple food items. A servo motor based meal assistance robot with 3 food containers was developed and kinematic modeling was carried out in order to facilitate the visual servoing task. As the next objective, SSVEP based user intention detection system was developed using 3 stimuli frequencies (6Hz,7Hz,8Hz) and validated using 5 healthy subjects. SSVEP classification process was carried out using both Fast Fourier Transformation and Canonical Correlation Analysis. Using the FFT method, overall average classification time was around 29s. On the other hand, average classification time using CCA was around 9s and accuracy was around 90%. These data exemplifies the use of CCA for EEG classification in the proposed meal assistance robot.

According to the existing literature, another important objective to fulfill was the adaptive feeding capability. Feeding the food according to the user's mouth location was carried out by using a OpenCV based image processing algorithm. A wide angle camera was mounted on the end-effector of the robot and image data from the camera was used to identify the mouth location in the image frame and ultimately correct the spoon location according to the tracked mouth location. Proposed visual serving method was successfully able to classify and center according to the mouth position of every user the system tested with (at 100% accuracy). Furthermore, mouth open detection classifier was trained separately to identify the user's intention to consume food. OpenCV Haar classifier was trained using mouth open images and the trained classifier was able to successfully identify the mouth openings of the users (100% accuracy).

Finally the system was experimentally validated using healthy subjects. Five male subjects voluntary participated to validate the intention detection system while six male subjects were participated to validate the mouth tracking and mouth open detection system. Results from the intention detection validation experiments indicate that even-though FFT offer high levels of accuracy, it is not suitable to use due to the long classification times. CCA on the other hand provides the same level of accuracy while keeping the average classification time around 10s. This is a considerable improvement from the FFT based classification method which take more than 30s to classify the output. Mouth position tracking and open state detection system results indicate that systems performed at 100% accuracy for the all subjects. Even-though system underperformed at some lighting conditions, it performed at 100% accuracy in normal room lighting conditions.

Despite the availability of few commercial meal assistance robots, the need for improvements is important in many ways. One of the major drawbacks of current meal assistance robots is the control method they are using. Also fix point feeding is an another important aspect to solve in order to increase the usability of the system. Therefore, this research can be stated as an attempt to address those drawbacks and increase the effectiveness of meal assistance robots. Moreover, according to the literature reviewed in the thesis process, this is the first time a application of EEG was carried out for a meal assistance robot with a adaptive feeding capability.

7.2 Future directions

Even-though the proposed EEG based BMI of the meal assistance system has given promising results following suggestions can improve the usability of the system for the user.

- Further studying the capability of decreasing false classification rates will improve the reliability of the system even more. Furthermore, emphasis should be given to decrease the false classification rate at the rest state.
- Investigating the possibility of using dry electrode technology is important to reduce the un-comfortability of the user when wearing the electrode for longer period of time. Additionally dry electrodes will reduce the preparation time significantly which will make the system more plug and play.
- Testing the proposed system with end users will be essential in validating the proposed design. It will give new insights on modifying the current system to best suit disabled individuals.

Appendix A

FIRST APPENDIX

A.1 Forward kinematics equations

```
def converteJ1(x):
    if x>4100:
        anglez = ((math.pi*0.52777777778)/3900)*(x-4000)
    if x<4100:
        anglez = 0
    if x==4100:
        anglez = 0
    return anglez

def converteJ2(x):
    if x>=4000:
        anglez = -((math.pi*0.52777777778)/4000)*(x-4000)-0.22222222222*math.pi
    return anglez

def converteJ3(x):
    if x>5500:
        anglez = ((math.pi*0.55555555556)/2500)*(x-5500)
    if x==5500:
        anglez=0
    if x<5500:
        anglez= ((math.pi*0.36666666667)/1500)*(x-5500)
    return anglez

def convertT1T2T3(T1,T2 , T3):
    print 'from convert T123' , T1,T2 , T3
    if T1 >0:
        T1=math.radians(T1)
        S1=T1/((math.pi*0.528)/3900)+4000
    if T2 <0:
        T2=math.radians(T2)
        S2 = 4000 - (T2+0.22222222222*math.pi)/((math.pi*0.52777777778)/4000)
    if T3 > 0:
        T3=math.radians(T3)
        S3 = T3/((math.pi*0.556)/2500) +5500
    if T3 < 0:
        T3=math.radians(T3)
        S3 = T3/((math.pi*0.367)/1500) +5500
    if T3 == 0:
        S3 = 5500
    return S1 , S2 , S3
```

```
def FKout():
    servo=Mastro_controller.Controller()

    THETA1= converteJ1(servo.getPosition(1))
    THETA2= converteJ2(servo.getPosition(2))
    THETA3= converteJ3(servo.getPosition(3))
    l1=265;
    l2=250;
    l3=87;
            X = l1 * math.cos(THETA1) + l2 * math.cos(THETA1 + THETA2) + l3*math.cos(THETA1 + THETA2 +
THETA3);
    theta = THETA1 +THETA3 + THETA2
    Y = l1 * math.sin(THETA1) + l2 * math.sin(THETA1 + THETA2) + l3*math.sin(THETA1 + THETA2 +
THETA3);

    return X,Y,theta
```

A.2 Inverse kinematics equations

```
def IKCal(X,Y,Theta):
    x=float(X)
    y=float(Y)
    Phi=float(Theta)
    L1=265;
    L2=250;
    L3=87;

    Px=x-L3*math.cos(math.radians(Phi));
    Py=y-L3*math.sin(math.radians(Phi));
    R=math.sqrt(Px*Px+Py*Py);

    Beta1= math.degrees(math.atan(Py/Px));
    Psi=math.degrees(math.acos((Px*Px+Py*Py+L1*L1-L2*L2)/(2*L1*R)));
    Theta1=Beta1+Psi;

    Beta2= math.degrees(math.atan((Py-L1*math.sin(math.radians(Theta1)))/(Px-
L1*math.cos(math.radians(Theta1)))));

    Theta2=Beta2-Theta1;
    Theta3=Phi-Theta1-Theta2

    return Theta1 , Theta2 , Theta3
```

LIST OF PUBLICATIONS

- C. J. Perera, I. Naotunna, C. Sandaruwan, R. Gopura, and T. D. Lalitharatne, "SSVEP based BMI for a meal assistance robot," in 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Budapest, Hungary, 2016, pp. 2295-2300.

- I. Ruhunage, C. J. Perera, N. Kalinga, J. Subodha, T. D. Lalitharatne, "EMG signal controlled transhumerai prosthetic with EEG-SSVEP based approch for hand open/close," in 2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Calgary, Canada, 2017, pp. 3169-3174.

- C. J. Perera, T. D. Lalitharatne, and K. Kiguchi, "EEG-controlled meal assistance robot with camera-based automatic mouth position tracking and mouth open detection," in 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, 2017, pp. 1760-1765.

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