Using Brain-Computer Interfaces to Interact with a Smart Home Environment

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Media Computing Group
Prof. Dr. Jan Borchers
Computer Science Department
RWTH Aachen University

by
Sarah Suleri

Thesis advisor:
Prof. Dr. Jan Borchers

Second examiner:
Prof. Dr. Bastian Leibe

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Abstract

This research investigated using thought as a modality to control a smart home environment. For this purpose, it was vital to look into how thought as a modality is perceived by different people as compared to other means to interact with a smart home environment. Upon comparison with voice, touch, gestures and manual interaction, thought as a modality was found to be the most preferred option.

In order to create a brain-computer interface that uses thought as a modality to control a smart home environment, the first step was to investigate the generalizability of the neural signals acquired against the thoughts to control everyday devices. In a preliminary study, we investigated the generalizability of neural-signals acquired against four tasks of switching on/off a given/imaginary light. As per the obtained accuracy level of classification, it was deduced that the acquired signals are classifiable but only to a level a bit higher than chance. Also, the obtained results were the same for the signals acquired against the tasks related to a specific light as opposed to any light the subject could imagine.

The results of the preliminary study lead to two more studies with extended scope of investigation and also a few changes in the study setup such as introduction of curtains and noise cancellation headphones to minimize external distractions. We used pre-recorded instructions for the participants to ensure consistency. Neural-signals were recorded against 34 different tasks related to interacting with 6 different everyday devices. Namely, light, fan, television, air conditioner, thermostat and door. As per the Subject-Independent (30 users) and Subject-Dependent (1 user) studies conducted, it was observed that simple and concrete tasks such as turning a specific device on or off, turning a specific value such as volume, channel or temperature up or down, were relatively easier to imagine for subjects. The classification results also supported this claim by providing the highest level of accuracy for these tasks. It was reported that tasks with vague terms such as cool, moderate and warm for temperature or switching to a specific TV channel by name, were hard to imagine for users. In totality, Random Forest obtained the highest and kStar provided the least level of accuracies for approximately 85% of the time.

Acknowledgements

I would like to dedicate my thesis to my sister, without whom, this thesis would not have been possible. Thank you for being a constant source of amazing and completely mind blowing ideas. Above all, thank you for making me believe that I can achieve anything and everything in life.

Secondly, I would like to thank Christian L. Corsten. Thank you for being my biggest inspiration and my toughest critic. I have learned a lot from you. Thank you for having faith in me, for having perpetual patience and for giving me the independence to make my own choices and to learn from my own mistakes. Thank you for being an amazing mentor, I would not have been here, if it wasn't for you.

Lastly, I would like to thank all the participants who took part in the user studies. Thank you very much for your time, patience and constructive feedback. It helped me a lot during the entire course of my thesis.

Thanks a million,
– S

Conventions

Throughout this thesis we used the following conventions.

Text conventions

Definitions of technical terms or short excursus are set off in coloured boxes.

Excursus:
Excursus are detailed discussions of a particular point in a book, usually in an appendix, or digressions in a written text.

Definition:
Excursus

Source code and implementation symbols are written in typewriter-style text.

`myClass`

Chapter 1

Introduction

Home is one place where we feel the most comfortable and safe. It is not just a comfortable bed or a cosy couch that makes us feel relaxed. It is not just the locks on our doors that make us feel secure. It is much more than that. Our homes give us serenity, comfort, safety and most of all, an ease of being the way we want to be.

Our homes make us feel comfortable and safe.

While our sentiments towards our homes remain the same, the way our homes take care of us has evolved over time. From wood burning fireplaces to thermostats that *learn* our desired temperature throughout the day. Times have clearly changed. Homes have become better and smarter [Olick, 2016].

Homes have evolved with the passage of time.

Nowadays, we have homes that are smart enough to *know*. Be it knowing to switch on a light when we enter a room, or turning the heating down when we leave the house. A smart home knows and adapts accordingly. These smart homes use assistive devices, various kinds of sensors and the communication between them to provide their residents with comfort, convenience and security [Sama, 2016].

Nowadays, we have homes that are smart enough to *know* the needs of its inmates.

Let us take the idea of a smart home one step further. How about having a home that is smart enough to know what you are thinking? A home that understands what you want. Not only that, a home that changes the environment according to your thoughts. A smart home environment

How about having a smart home environment that is controlled solely by your thoughts?

that is controlled solely by your thoughts. Is it possible? How is it possible? Would it actually work? is what this thesis is all about.

We propose to use thought as a modality to interact with a smart home environment.

In our research, we propose a brain-controlled smart home environment. We suggest using human thoughts as means to interact with devices of everyday use. Simply put, ”You think and the light turns on”. This research investigates how brain-computer interfaces can be used to interact with a smart home environment. Before getting into details of the main idea proposed in this thesis, let us answer a few basic questions.

1.1 What are Brain Computer Interfaces?

Brain-Computer Interfaces (BCI) also known as the Mind-Machine Interfaces (MMI), Direct Neural Interfaces (DNI) or Brain-Machine Interfaces (BMI) can be defined as:

Definition: *Brain Computer Interfaces*

BRAIN COMPUTER INTERFACES:
Brain-Computer Interfaces (BCI) are interfaces that use human thoughts to interact with machines [Tan and Nijholt, 2013].

For the purpose of simplicity, we are going to use the term **BCI** for Brain Computer Interfaces, throughout this thesis document.

”The BCI systems use thoughts as a control mechanism.” [Masood et al., 2016]

To briefly explain the concept of BCI, we can say that whenever a person thinks, there is a certain pattern of neural signals generated in his mind. Since BCI uses thoughts as input, there is a need to read the corresponding neural signals. BCI uses certain number of electrodes to read these electrical signals. Once these signals are acquired, they are translated into commands that a machine can understand [Guruprakash et al., 2016]. As of now, we will not discuss the details of this thoughts-to-command translation process. However, the whole process of how thoughts are translated into machine understandable commands is explained in detail in Section 1.2 – How does

BCI work?.

To further explain the concept of BCI, let us consider a simple example shown in Figure 1.1. The figure shows a person thinking about ”turning on a light”. His thoughts are taken as input into BCI, which then translates these thoughts into an ”ON” command for the light bulb. As a result, the light turns on.

”BCI is a communication pathway between the brain and the external peripheral devices.” [Verlekar et al., 2016]

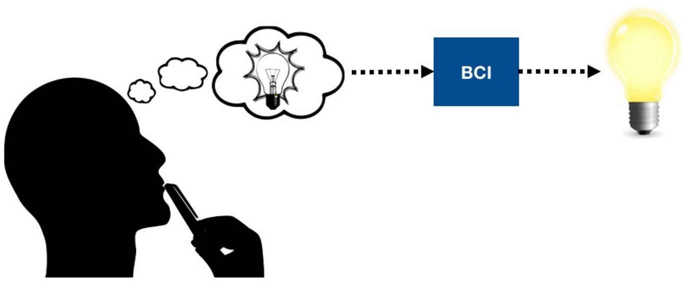


Figure 1.1: BCI system using human thought as input to interact with an everyday device (light bulb)

Having given a brief introduction to BCI, let us now get into the internal details of how BCI translates thoughts into machine understandable commands.

1.2 How does BCI work?

Figure 1.2 shows various phases of BCI at a glance. The neural signals have to go through each phase in order to get translated into machine understandable commands.

Briefly put, the translation process starts when a person thinks about a task. The neural signals generated against his thoughts are acquired in a process called *Signal Acquisition*. Once these signals are recorded, they are passed onto the next phase called *Pre-processor*. The pre-processor is responsible for enhancing the quality of these signals. After doing so, the pre-processor passes these signals to *Decoder*. Lastly, the decoder classifies these signals into machine understandable commands.

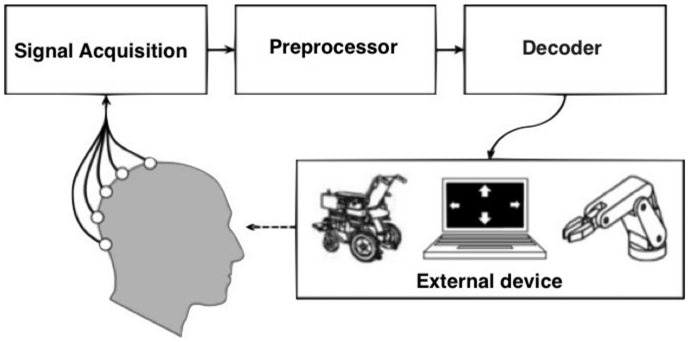


Figure 1.2: Phases of BCI scheme at a glance [Mora-Cortes et al., 2014]

Let us now dig a bit deeper into the internal details of each phase of BCI.

1.2.1 Signal Acquisition

Signal Acquisition is the first and most vital step of the entire BCI scheme. It can be defined as:

Definition: *Signal Acquisition*

SIGNAL ACQUISITION:
The process of recording neuro-signals against any thought using any brain activity recording device is called signal acquisition [Nicolas-Alonso and Gomez-Gil, 2012].

There are two ways to acquire neural signals generated against thoughts. The first signal acquisition method requires surgically implanting electrodes, whereas the second method uses electrodes externally. Based on the method used for signal acquisition, BCI is categorized into the following two types:

1. Invasive BCI

2. Non-invasive BCI

Invasive BCI can be defined as:

INVASIVE BCI:
BCI that requires implanting of external electrodes in the subject's brain for signal recording is known as invasive BCI [Nicolas-Alonso and Gomez-Gil, 2012].

Definition: *Invasive BCI*

The greatest advantage of invasive BCI is the high quality of the obtained signals. However, this technique suffers from a lot of issues. Aside from usability issues rising from the involvement of a surgical procedure, the implanted electrodes can only read signals from specific and small sized regions i.e. where they are surgically implanted. Once planted, these electrodes cannot be shifted to measure the electrical activity in any other brain region. This makes the recording method very tedious and highly limited[Abdulkader et al., 2015].

Although non-invasive BCI provides high quality neural signals but they can only read signals from specific regions i.e. where the electrodes are surgically implanted.

An alternative method to acquire the brain signals is to place the electrodes on top of the human head using a BCI headband or an electrode cap. This type of BCI is called *non-invasive BCI*. Non-invasive BCI can be defined as:

Non-invasive BCI acquires signals by placing electrodes on top of human head.

NON-INVASIVE BCI:
BCI that does not require implanting of external objects into subject's brain for acquiring signals is called non-invasive BCI [Abdulkader et al., 2015].

Definition: *Non-invasive BCI*

Figure 1.3: Emotiv Epoc[1], a non-invasive BCI headband with 14 electrodes for signal acquisition.

Non-Invasive BCI Headbands

There are a few non-invasive BCI headbands that are commercially available and are cost effective. There is Emotiv Epoc[1] with 14 electrodes (cf. Figure 1.3), Interaxon MUSE[2] with 4 electrodes and NeuroSky[3] with 1 electrode.

The neural signals acquired by invasive and non-invasive method are noisy [Nicolas-Alonso and Gomez-Gil, 2012]. Therefore, these signals need to undergo a few signal enhancement processes and for this purpose, they are passed onto the next phase of the BCI scheme known as pre-processor.

1.2.2 Pre-processor

Once the signals are recorded against any thought, they go through a pre-processing phase for signal amplification and noise reduction. Signal pre-processing can be defined as:

Definition: *Signal Pre-processing*

SIGNAL PRE-PROCESSING:
The process of signal manipulation by performing signal enhancement and noise reduction to extract the valuable information out of the signals is called signal pre-processing. [Nicolas-Alonso and Gomez-Gil, 2012]

By reducing signal noise, the pre-processor phase ensures a decrease in the size of data passed on to the next phase known as decoder.

1.2.3 Decoder

Once the pre-processor has provided the decoder with noise free signals, the next step is to extract the relevant information as per need.

[1] https://www.emotiv.com/epoc
[2] http://www.choosemuse.com
[3] http://neurosky.com/biosensors

Nicolas-Alonso and Gomez-Gil [2012] stated that the acquired neural signals consist of various frequency ranges known as *Frequency Bands*. Namely, delta δ (1 – 3Hz), theta θ (4 – 7Hz), alpha α (8 – 12Hz), beta β (12 – 30Hz) and gamma γ (30 – 100Hz). Each frequency band represents a specific *feature*. A signal feature can be defined as:

Neuro-signals consist of δ, θ, α, β and γ frequency bands. Each representing a specific feature.

SIGNAL FEATURE:
Each brain signal acquired against a thought can be divided into various frequency ranges known as features [Nicolas-Alonso and Gomez-Gil, 2012].

Definition: *Signal Feature*

Each frequency range contains information related to a different aspect of human thinking. For example, the Beta rhythms β ranging from 12Hz to 30Hz are related to motor activities, more specifically the visualization of motion.

Each feature contains information about a certain aspect of human thinking.

It is very important to know what information is desired to be extracted out of the acquired signals. Feeding the decoder with extra and redundant information is not a wise choice. Hence, the acquired signals go through the next step of *Feature Extraction*.

FEATURE EXTRACTION:
The process of extracting the signals belonging to a specific frequency range, as per need is called feature extraction [Nicolas-Alonso and Gomez-Gil, 2012].

Definition: *Feature Extraction*

Once the desired features are extracted, the signals are ready to be classified in the next step known as *Signal Classification*. Signal classification is the last step of translating thoughts into machine understandable commands. The signal classifier is provided with certain extracted features of the acquired signals. The classifier is then responsible for classifying these signals into commands in a process called signal classification.

SIGNAL CLASSIFICATION:
Signal Classification is used to train BCI to translate user intent into machine understandable commands [Abdulkader et al., 2015].

Definition: *Signal Classification*

Classified signals become a part of the Control Interface as commands.

Once the thoughts to commands translation process is complete, the classified signals become a part of the control interface as commands. The control interface is an interface that provides the user with all the commands the system has to offer. The end user can use these commands to interact with the respective machine.

The above mentioned steps are what constitute BCI. Besides being invasive or non-invasive, BCI is also differentiated on the basis of whether it is trained by one or multiple users. This criterion classifies BCI into *Subject-Dependent* and *Subject-Independent* BCI.

1.3 Subject-Dependent vs Subject-Independent BCI

Non-invasive BCI requires initial configuration.

Considering the case of non-invasive BCI, the user is asked to record his thoughts against certain commands. He is required to perform this recording process repeatedly, in order to train BCI classifier. As mentioned previously, training the BCI classifier enables it to map thoughts to commands. We shall refer to this training process as *Initial Configuration* of BCI.

Subject-Dependent BCI require initial configuration by a single user.

In case of *Subject-Dependent* BCI, the initial configuration is performed by only one user. For a particular command set that the system provides, one user is asked to record his thoughts repeatedly. This trains the BCI classifier for the thoughts of that particular subject, thus making BCI optimized for that specific user. Figure 1.4 gives an overview of how a Subject-Dependent BCI works.

Subject-Independent BCI follows one-size-fits-all approach, where the end user gets a pre-trained system.

There is an alternative to the Subject-Dependent approach known as *Subject-Independent* BCI. Unlike the Subject-Dependent BCI, the Subject-Independent BCI follows the one-size-fits-all approach [Fazli et al., 2009]. This means that the Subject-Independent BCI is pre-trained to be used by anyone. Figure 1.5 gives an overview of a Subject-Independent BCI. Here the term end user refers to the user who uses the BCI system but is not involved in the training

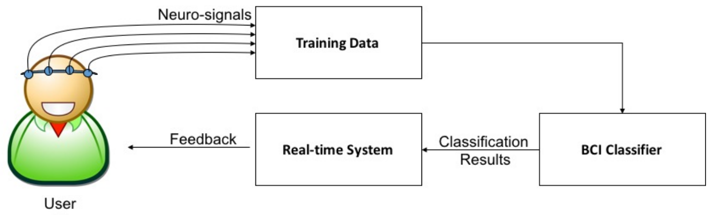


Figure 1.4: Overview of a Subject-Dependent BCI. Neuro-signals acquired from one user are used to train the BCI classifier. Upon usage, the user gets system feedback based on the classification results of the BCI classifier.

process of the BCI classifier.

In the Subject-Independent BCI, the end user is provided with a pre-trained system. The end user can readily use this pre-trained system without performing any initial configuration. In this approach, when the user thinks about a certain command, the system recognizes the thought pattern and identifies the command that corresponds to that particular thought pattern. These systems as the name suggests are independent of who is using them.

The Subject-Independent BCI is pre-trained by the signals acquired from multiple users.

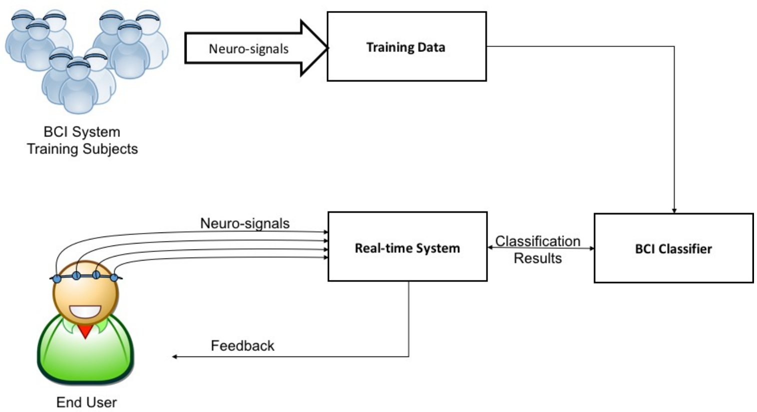


Figure 1.5: Overview of a Subject-Independent BCI. The system is trained by the signals acquired from multiple users. The end user uses a pre-trained system and gets real-time feedback based on the classification results of the BCI classifier.

The question remains that if the end user does not go through the step of the initial configuration then how exactly are these systems pre-trained? To answer this question, let us look into the two parts of Subject-Independent BCI.

1. An offline training part; where the BCI classifier is trained using the signals acquired from a significant amount of users.

2. An online part; where the end user actually uses the pre-trained system and gets feedback in real time.

Having introduced the concept of BCI, the different phases involved in BCI and the classification of BCI on the basis of user training, we can now proceed towards the research questions investigated in this thesis.

1.4 Research Questions

The aim of this research is to investigate the use of BCI as means to interact with a smart home environment. BCI systems are designed and used not only by people with impairment but also by users with no physical or mental disability. However, the scope of this thesis has been limited to a user base with no physical or mental disability.

The main research question addressed in this thesis is:

- Can a smart home environment be controlled by a non-invasive BCI?

In order to answer this research question, we needed to investigate the following few questions:

- **What do people think before doing an action related to controlling a device of everyday use?**
  The purpose of this question is to find out the thought process behind any given task to interact with an everyday device. In a preliminary study, we will gather various ways in which different users imagine a given task to interact with a device of everyday use. For example, one task can be to think about turning on a light. The information regarding the thought process behind a certain task will be obtained by asking each participant of the preliminary study to explain in his own words how he imagined that task. The answer to this research question will help us in formulating further tasks related to controlling other devices of everyday use. More importantly, the answer to this question will enable us to breakdown tasks to the simplest level for further studies i.e. Subject-Independent (cf. Chapter 6) and Subject-Dependent (cf. Chapter 7) study.

We investigate the **thought process** behind an action, the **time taken** to think and the **repetitiveness** of a thought to control an everyday device in a preliminary study.

- **How long does a person take to think about a certain task related to controlling a device of everyday use?**
  The purpose behind finding out the time taken by a person to think about a certain task related to controlling an everyday device is to calculate a *window size*. The window size refers to the average time taken to think about a certain task. During the preliminary study, every subject will be provided with a few tasks to imagine. As mentioned previously, these tasks will be related to controlling a device of everyday use such as a light. The time taken by each user to imagine each task will be recorded. The average of the recorded time periods will give us the window size. Having a specific window size helps us in knowing for how long do we need to record the neuro-signals against one task. Recording the neuro-signals for a specific window size limits the amount of sensory information we extract out of the subject's brain [Tan and Nijholt, 2013]. The window size we will obtain

from the preliminary study will be used as a parameter for recording the neuro-signals in both, Subject-Independent (cf. Chapter 6) and Subject-Dependent (cf. Chapter 7) study.

- **When thinking about a particular action repeatedly, do people think the same every time?**
The purpose of this question is to investigate the uniqueness of the thought process of every person individually. In the preliminary study, each task given to every subject will have 3 iterations. Using Thinking Aloud technique, we investigate how similarly or differently a person thinks about a particular task with each iteration. We further investigate the uniqueness of thoughts of one subject in the Subject-Dependent study where neuro-signals acquired from only one subject are classified and examined for uniqueness.

Subject-Dependent study investigates the uniqueness of thoughts of a single subject.

- **Is the thought process of different people behind a particular action to control an everyday device, unique?**
The purpose of this question is to compare and contrast the thought process of different people to determine whether every person thinks uniquely or not. The answer to this question will help us in finding out if thoughts are generalizable among different people. In the Subject-Independent study, we investigate the uniqueness of the neural-signals acquired against thoughts to control various devices of everyday use in a smart home environment. These neuro-signals are acquired from multiple users. Once acquired, the recorded signals are processed and classified to attain the level of accuracy to which they are classifiable. The accuracy level of classification of the acquired neural signals identifies their generalizability.

We investigate the uniqueness of thoughts among different people in the Subject-Independent study.

The answers to the above mentioned research questions enable us to know that if a smart home environment is controlled by non-invasive BCI, then how accurately would that system work.

1.5 Outline

The thesis is organized into the following chapters:

- **Chapter 2.** Various research projects related to non-invasive BCI used to control devices of everyday use in a smart home environment are discussed and contrasted with the research conducted in this thesis.
- **Chapter 3.** Details of a comparative study between various modalities to control a smart home environment are discussed. The purpose of this study is to investigate how thought as a modality is perceived by different people.
- **Chapter 4.** Before conducting any study to answer the research questions, it was important to take a few decisions regarding the kind of neuro-signals we required, the BCI headband needed to obtain those neuro-signals and the tools to be used in development of the BCI system we aimed to create. The choices made, the procedures selected for the study and the justification of these choices are discussed.
- **Chapter 5.** Details of a preliminary user study conducted are discussed. This study addresses the research questions related to the thought process behind an action, window size and the repetitiveness of a thought. This formulates a foundation for the further studies performed.
- **Chapter 6.** An expansion of the preliminary study was a Subject-Independent user study. Details of this study, the scope, the major changes in the study design and a few additional observations are discussed. This study investigates the research question related to the uniqueness of thoughts among different people.
- **Chapter 7.** In order to contrast the results of the Subject-Independent study, a Subject-Dependent user study was conducted. Study design and procedural details are discussed. This study addresses the uniqueness of thoughts of a single subject.

- **Chapter 8.** Comparison and contrast of the findings of the Subject-Independent and Subject-Dependent user studies is discussed.
- **Chapter 9.** A summary of the overall contribution as well as the possible future steps this research can take, are presented.

Chapter 2

Related work

The idea of using non-invasive BCI in the context of home automation has been around for a couple of years. In this chapter, we shall explore various research projects related to this concept. We shall also discuss the existing gap in this research and how this thesis aims to fill that gap.

2.1 Control of a Smart Home with a BCI

Guger et al. [2008, 2012] suggest a non-invasive Subject-Dependent P300 stimulus based BCI system which provides the subject with a stimulus and records his reaction as an input. The user is provided with a GUI with various icons representing different tasks like turning a light on/off, opening a door/window and switching TV channels etc. (cf. Figure 2.1). In the worst case scenario, this system obtained 30% accuracy with 12 participants. Whereas, in best case scenario, one of the subjects achieved 100% accuracy.

”**P300** BCIs rely on selective attention to visual stimuli... Whenever user focuses attention on a specific stimulus, a brainwave called the P300 may occur...” – [Tan and Nijholt, 2013]

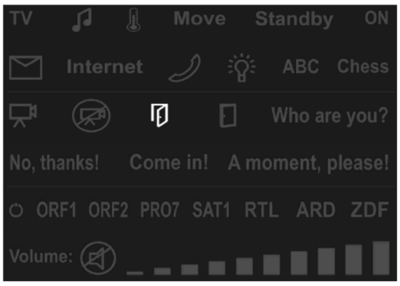


Figure 2.1: GUI containing various icons representing different household tasks [Guger et al., 2008]. User's reaction is recorded when a desired icon is flashed as a stimulus and corresponding task is performed.

2.2 Home Smart Home: BCI Control for Real Smart Home Environments

A non-invasive visual P300 based BCI system for disabled users to control a smart home using a 6x6 Matrix of icons.

Carabalona et al. [2010] suggest a non-invasive visual P300 based BCI system for physically impaired users to control a smart home environment. The user is provided with a 6x6 matrix of icons (cf. Figure 2.2). Each icon represents a command related to an everyday device. The icons flash on the computer screen one by one. Once a desired icon is reached, there is a peak observed in the neural signals of the user. This peak is considered as an icon selection. The system was tested by 4 participants and accuracy rate varied from 33% to 100% among different users.

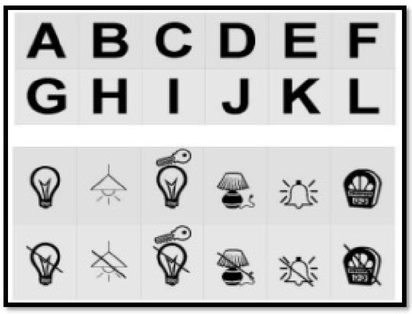


Figure 2.2: 6x6 matrix of icons representing different household tasks [Carabalona et al., 2010]. Upon flashing of a desired icon, user's reaction is recorded and considered as input.

2.3 Brain-Computer Interface for TV channel control

Kim et al. [2013] suggest a non-invasive P300 stimulus based BCI system to switch TV channels from a viewing distance of 3 meters and a TV screen size of 46 inches. 8 subjects were provided with a visual stimulus by flashing a green cursor on the top left corner of each channel icon (cf. Figure 2.3). Once the desired channel is reached, a peak in the subject's neural signals was considered as input for channel selection. The system obtained an average of 92.3% accuracy.

A non-invasive P300 stimulus based BCI system to switch TV channels.

Figure 2.3: Interface for channel selection on TV Screen [Kim et al., 2013]. Green cursor on the top left corner of each channel icon flashes to invoke a response from the user.

2.4 BCI based Smart Living Environmental Auto-adjustment Control System

Ou et al. [2012] and Lin et al. [2014] suggest using user's mental state (drowsiness or alertness) to interact with the smart home environment around him. They propose a system called BCI-based Smart Living Environmental Auto-adjustment Control System (**BSLEACS**). Figure 2.4 shows the system architecture of BSLEACS. This system has the potential to extend its functionality using the Universal Plug and Play (UPnP) home networking.

BSLEACS takes user's mental state as input.

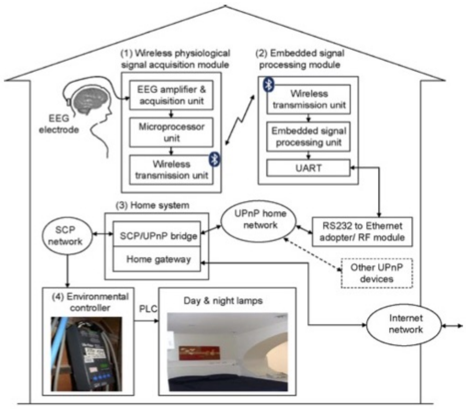


Figure 2.4: System architecture of BSLEACS [Lin et al., 2014]

2.5 Brain Controlled and Environmental Auto adjustment Smart Home Network

BCI that uses two physiological states (drowsiness or alertness) of users and translate them into commands to interact with different electronic appliances.

Similar to the system proposed by Lin et al. [2014], Pradeep and Padmajothi [2015] suggest using non-invasive Subject-Dependent BCI to control electrical home appliances. They also use two physiological states (drowsiness or alertness) of users and translate them into commands to interact with different electronic appliances. Figure 2.5 shows the proposed system architecture of the brain controlled Smart Home Network.

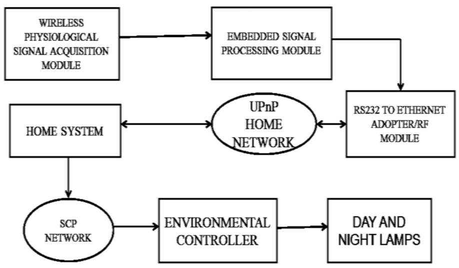


Figure 2.5: System architecture of the brain controlled Smart Home Network. The model mainly consists of a wireless signal acquisition module, an embedded signal processing module and a host system [Pradeep and Padmajothi, 2015].

2.6 Vision: Smart Home Control with Head-Mounted Sensors for Vision and Brain Activity

Simoens et al. [2014] suggest a non-invasive Subject-Dependent BCI system that uses head-mounted vision sensors along with neural signals to control a smart home environment. The idea is to look at a device and make facial expressions to represent the command. The line of sight is detected by using head-mounted sensors for vision and the desired command is recognized by various facial expression detected by the Emotiv Epoc neuro-headband. The computation load is offloaded to a smart phone or a home cloudlet. Figure 2.6 shows an overview of the Smart Home Control system with BCI and head-mounted sensors for Vision. The major limitation of the proposed system is a scenario where multiple devices are in view.

A non-invasive Subject-Dependent BCI system that uses a head-mounted camera to detect the device in sight and facial expressions to distinguish commands.

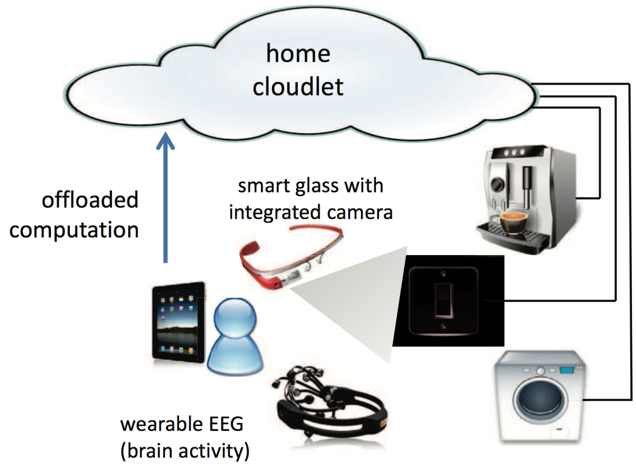


Figure 2.6: Overview of the Smart Home Control system with BCI and Head-Mounted Sensors for Vision [Simoens et al., 2014].

2.7 Region Based Brain Computer Interface for A Home Control Application

A non-invasive P300 stimulus based BCI system that follows region based selection paradigm.

Aydin et al. [2015] suggest following region based selection paradigm for a smart home control application for physically impaired users. As per the region based selection paradigm, the application screen is divided into various regions. Each region represents a different task related to smart home control. The proposed system is a non-invasive P300 stimulus based BCI system that flashes each region 5 times on the screen to invoke a response from the user. Upon acquiring a peak in the neural signals of the subject, the system considers it as a selection command for that particular region. The proposed system reached 95% accuracy for 49 household tasks using 5 subjects without any physical impairment.

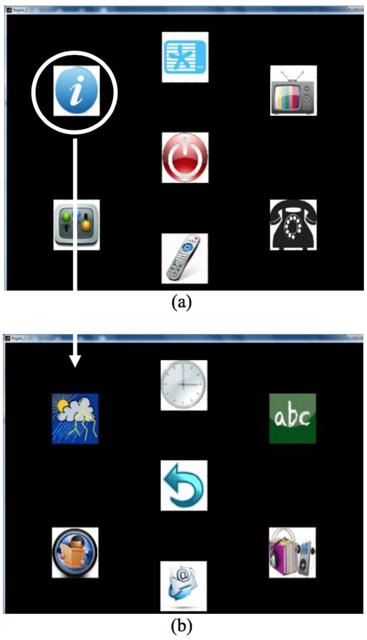


Figure 2.7: Region Based BCI for a Home Control Application. **(a)** Each icon represents a region. Upon flashing of the desired icon, a peak in subject's neural signals is observed. **(b)** As a result, the flashing icon is selected and the screen shows further options [Aydin et al., 2015].

2.8 Smart Home for Disabled Using BCI

Sharma and Sharma [2015] suggest a non-invasive Subject-Dependent BCI system for physically impaired users that uses a variation of EEG and FNIRS neural signals obtained from the area near the subject's eyes. The acquired neural signals are used as input to interact with a web interface to control and monitor alarm sensors for temperature, fire, light, water and in-path obstacles. Upon activation of any alarm, the user receives an alert.

A non-invasive Subject-Dependent BCI that uses neural signals to control and monitor temperature, fire, light, in-path obstacles and water sensors.

2.9 Using BCI for Home Automation

Verlekar et al. [2016] suggest using a non-invasive BCI to control various home appliances. EEG neural signals are recorded using electrodes placed at the motor cortex area of the subject. The proposed system provides the user with a GUI. The GUI enables the user to select a device he intends to interact with. In order to select a particular device, the user is required to concentrate. When the user concentrates beyond 18Hz, variations in frequency bands of his neural signals are considered as selection input.

A non-invasive BCI that uses concentration level of the user as input to interact with various smart devices.

2.10 BCI based Smart Home Control using EEG Signals

Masood et al. [2016] suggest using a non-invasive BCI that uses blink of an eye as a control input to interact with home appliances. They used NeuroSky EEG headband to read brain signals. The selection and control of the device is performed using a GUI. The system requires the user to blink thrice in order to get activated. Once activated, the user has 5 seconds window to blink twice to turn on a specific device. After 5 seconds, the focus moves onto the next device. The paper also discusses controlling the fan speed between fast, medium and slow using various meditation levels of the user. For example, having a meditation value below

A non-invasive BCI system that uses eye blinking and meditation levels of the user as control input to interact with a smart home.

33 will define the fan speed as slow. Once, the focus has passed all the devices available on the GUI, the system is deactivated automatically. The system has the potential to be enhanced by adding more devices. However, the current proposed system has 70% proficiency.

2.11 Brain Controlled Home Automation

Guruprakash et al. [2016] suggest a non-invasive EEG based BCI for disabled people that takes an eyebrow raise or a smirk as an input to emulate mouse click. The user is provided with a GUI to interact with a virtual home environment. The proposed system uses NeuroSky BCI headband to acquire neural signals against an eye blink to turn on a desired appliance.

Above mentioned are a few non-invasive BCI systems to interact with a smart home environment. We looked at various BCI systems approaching this idea in different ways, but there exists a gap. BCI research has yet to investigate a non-invasive BCI that follows the Endogenous Control Task Paradigm to control a smart home environment. Let us first define Endogenous Control Task Paradigm:

Definition:
Endogenous Control Task Paradigm

Endogenous Control Task Paradigm:
"In an Endogenous Control Task Paradigm, the user voluntarily performs a mental task that activates a particular part of the brain e.g. imagining hand movement" [Tan and Nijholt, 2013].

In order to create a non-invasive BCI that follows the Endogenous Control Task Paradigm to control a smart home environment, it is vital to first investigate thought as a modality. Chapter 3 discusses a study to investigate how different people perceive thought as a modality. It also compares thought with other modalities to interact with a smart home environment.

Chapter 3

Thought as a Modality

We intended to investigate how different people perceived thought as a modality to control a smart home environment. In order to do that we conducted a study with 13 users in which each participant was given 5 different scenarios. Each scenario dealt with a different modality used to control smart devices. The study inquired the users regarding the following means to interact with a smart home environment:

A comparative study to investigate how different people perceived thought as a modality as compared to other means of interaction with a smart home environment.

- Interacting **manually**
- Interacting using **voice** commands
- Interacting using **gestural** commands
- Interacting using a **touch** device
- Interacting using **thoughts**

Once a scenario was explained to the participant, he was asked to fill out a questionnaire related to that specific modality. The questionnaire (cf. Appendix A) was an adaptation of the NASA Task Load Index[1] questionnaire. For each given scenario, the participant was asked to answer each question using a 7-point scale.

[1]https://humansystems.arc.nasa.gov/groups/tlx

For each modality, the user was asked to report regarding the following:

3.1 Mental Demand

This question investigated regarding the mental demand of controlling a smart home environment using a particular modality. Figure 3.1 shows a graph of mean values of mental demand of each modality.

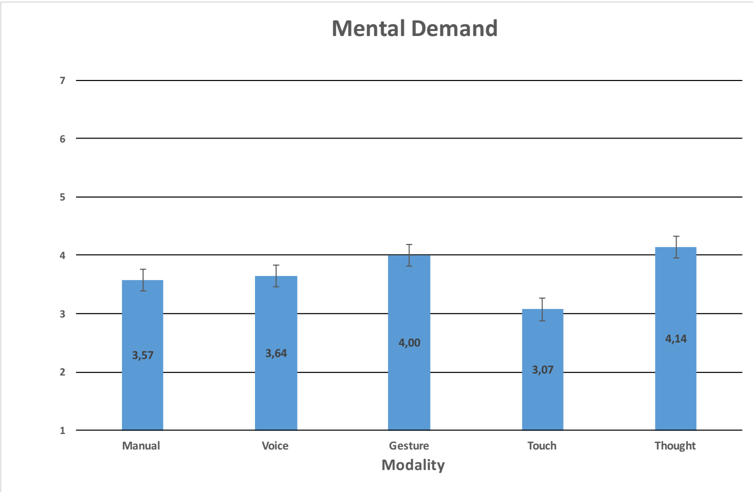


Figure 3.1: Mental demand of controlling a smart home environment using different modalities.

Thought as a modality (M = 4.14, SD = 2.34) showed the highest average as compared to other modalities. As per the results shown in figure 3.1, we can say that performing a task using thoughts would have the maximum mental demand.

3.2 Physical Demand

This question investigated regarding the physical demand of controlling a smart home environment using a particular modality. Figure 3.2 shows a graph of mean values of physical demand of each modality.

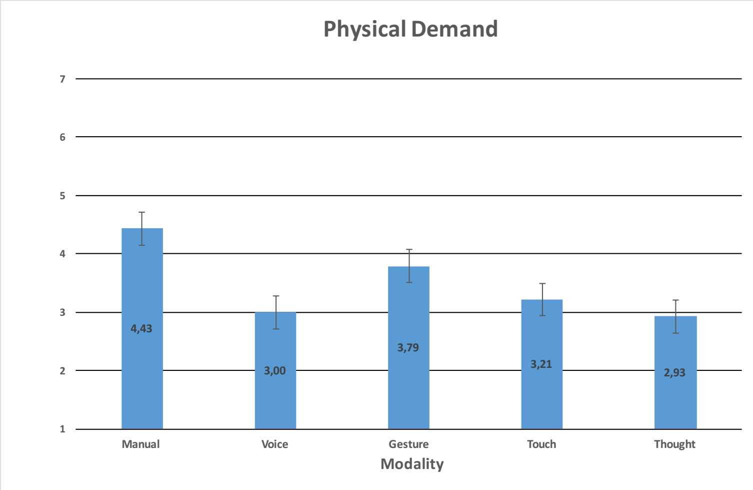


Figure 3.2: Physical demand of controlling a smart home environment using different modalities.

Performing a task **manually** (M = 4.43, SD = 1.74) showed the highest average. Whereas, **thought** (M = 2.93, SD = 2.3) as a modality showed the least value of mean as compared to other modalities. As per the results shown in figure 3.2, we can say that performing a task manually has the maximum physical demand. On the other hand, performing a task using thoughts has the least physical demand.

3.3 Temporal Demand

This question investigated regarding the temporal demand of controlling a smart home environment using a particular modality. Figure 3.3 shows a graph of mean values of temporal demand of each modality.

Performing a task **manually** (M = 4.5, SD = 1.45) showed the highest average. Whereas, **voice** (M = 2.71, SD = 1.43) and **thought** (M = 2.93, SD = 2.1) as modalities showed the least value of mean as compared to other modalities.

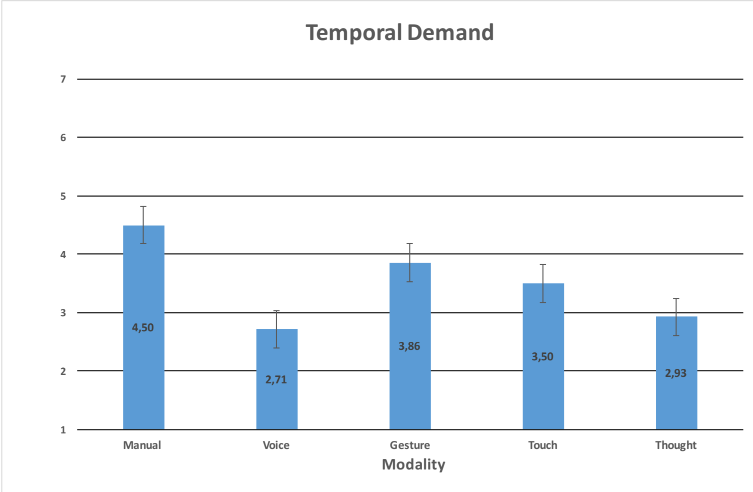


Figure 3.3: Temporal demand of controlling a smart home environment using different modalities.

As per the results shown in figure 3.3, we can say that performing a task manually is the most time consuming. On the other hand, performing a task using voice commands or thoughts has the least temporal demand.

3.4 Effort

This question investigated regarding the amount of effort required to control a smart home environment using a particular modality.

Figure 3.4 shows a graph of mean values of effort needed by each modality. Performing a task **manually** (M = 4.93, SD = 1.94) showed the highest average. Whereas, **voice** (M = 2.93, SD = 1.73) as a modality showed the least value of mean as compared to other modalities. **Thought** (M = 3.14, SD = 2.31) as a modality came in second to the voice modality.

As per the results shown in figure 3.4, we can say that performing a task manually requires the most effort. On the other hand, performing a task using voice commands or thoughts requires the least amount of effort.

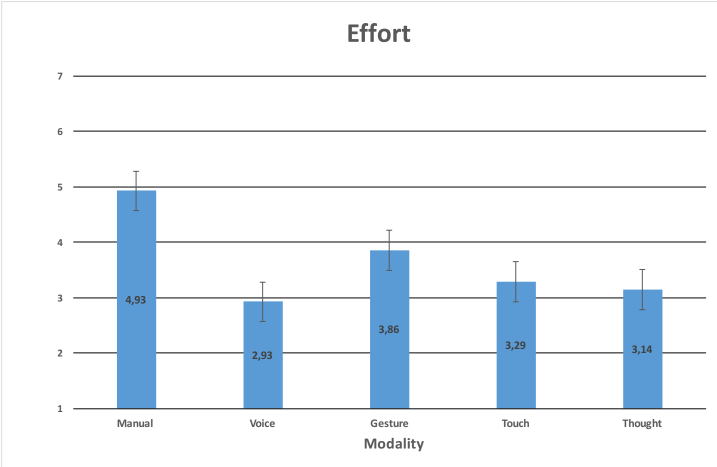


Figure 3.4: Effort needed to control a smart home environment using different modalities.

3.5 Preference

This question investigated regarding user preference for a modality to control a smart home environment. Figure 3.5 shows a graph of mean values depicting user preference for a modality.

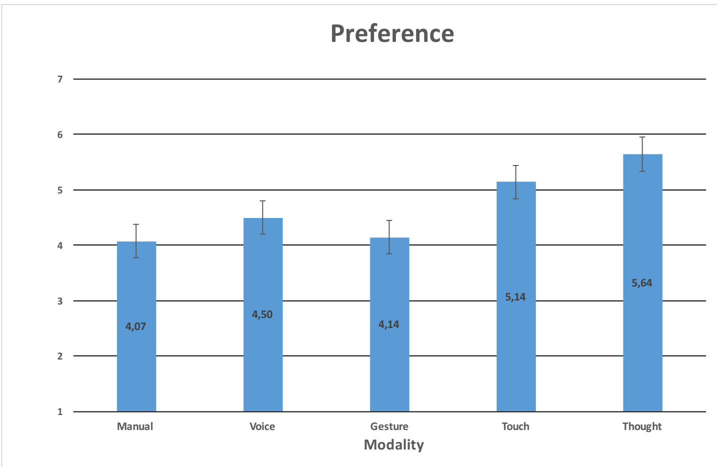


Figure 3.5: Preference for modality to control a smart home environment.

Using **thoughts** (M = 5.64, SD = 2.09) as a modality to interact with a smart home environment showed the highest average. Whereas, performing a task **manually** (M = 4.07, SD = 1.85) showed the least mean value. Therefore, we can say that using thoughts to interact with a smart home environment was the most preferred modality. On the other hand, performing the tasks manually was the least preferred option.

3.6 Qualitative Feedback

In addition to the questionnaire, the participants were also given the following situations where he could report his preference for a specific modality to interact with a smart home environment.

3.6.1 Alone

The participants were given the situation where they are alone at home. In this case, they were asked to report that out of the 5 previously mentioned modalities, which modality would they prefer to use. As per the qualitative feedback gathered, it was observed that participants did not have a clear preference in a scenario where they are alone at home. One of the participants reported:

> "When I am alone I don't really mind any (modality) actually." – **[P3]**

3.6.2 With People

The participants were given the situation where they have a few guests at home. In this case, they were asked to report that out of the 5 previously mentioned modalities, which modality would they prefer to use. As per the qualitative feedback gathered, it was observed that participants preferred to use the modality which did not require any *obvious* interaction.

One of the participants reported:

> ”When I am with people, I wouldn’t really want to do something stupid or embarrassing. So, I wouldn’t want to get up and do some gestures to turn on the light, for example. For this, I think, going and doing the task is fine. Even better would be thinking because then, I don’t even have to get up.” – **[P2]**

Another user reported:

> ”I have smart lights at home so to me it’s pretty normal to use my phone.” – **[P5]**

3.6.3 Busy

The participants were given the situation where they are busy doing something at home. In this case, they were asked to report that out of the 5 previously mentioned modalities, which modality would they prefer to use. As per the qualitative feedback gathered, it was observed that participants preferred to use the modality which required the minimum amount of time to interact.

One of the participants reported:

> ”If I am busy doing something, I wouldn’t want to do it by manually or make gestures. It depends, if my hands are free I wouldn’t mind using a touch device. But I think using voice or thoughts is much better. It’ll be quick and won’t disturb my work. ” – **[P8]**

Table 3.1 shows a summary of modality preferences in different situations.

Situation	Modality				
	Manual	Voice	Gesture	Touch	Thought
Alone	✓	✓	✓	✓	✓
With people	✓			✓	✓
Busy		✓			✓

Table 3.1: Summary of modality preferences in different situations.

3.7 Modality Comparison for Smart Home Control at a Glance

Figure 3.6 shows a comparison of the 5 modalities for all the 5 criteria at a glance.

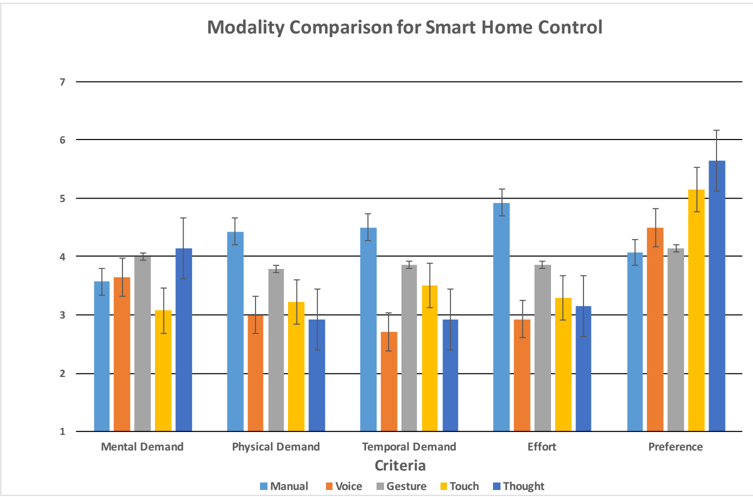


Figure 3.6: Comparison of Manual, Voice, Gesture, Touch and Thought input to control a Smart Home Environment.

Once we had found out how users perceived thoughts as a modality to control a smart home environment, we could move on to the next step. The next step involved figuring out various internal details of the BCI system we intended to investigate.

Chapter 4

Required Ingredients

Before we begin creating a BCI system to be used for any purpose, there are a few very important questions we first need to answer. The choices we make mainly depend on the purpose for which the BCI system is aimed to be used. We shall now go through these questions one by one, along with the reasoning behind the choices we made for our research.

4.1 Required Sensory Information

In our minds, the thoughts behind **intending** to do an action and actually doing an action are different [Tan and Nijholt, 2013]. Our goal was to capture the thoughts that are generated when a person thinks about doing an action. Therefore, we aimed to capture the information in a subject's mind regarding *Motor Imagery*. It can be defined as:

We intended to capture the thoughts generated when a person thinks about doing an action.

MOTOR IMAGERY:
Motor imagery is the imagination of motion, without doing any actual movement [Nicolas-Alonso and Gomez-Gil, 2012].

Definition: *Motor imagery*

Since the idea was to capture the neuro-signals generated against the thoughts of a user imagining a specific task, the corresponding signals we required were the *Sensorimotor Rhythms*.

Definition: *Sensorimotor Rhythms*

SENSORIMOTOR RHYTHMS:
"[...] modulation patterns in the motor rhythms that are produced as a result of mental rehearsal of a motor act without any overt motor output" [Nicolas-Alonso and Gomez-Gil, 2012].

Sensorimotor rhythms are suitable to create an endogenous BCI.

The sensorimotor rhythms are independent of any external stimuli and can be generated at free will [Tan and Nijholt, 2013]. These reasons make sensorimotor rhythms a suitable choice for creating an endogenous BCI to control a smart home environment.

Once we knew what kind of sensory information we required, the next step was to find out which regions of brain provided the information regarding the sensorimotor rhythms.

4.2 Regions of Brain

Figure 4.1 shows various regions of human brain and the association of these regions with the motor and sensory cortices.

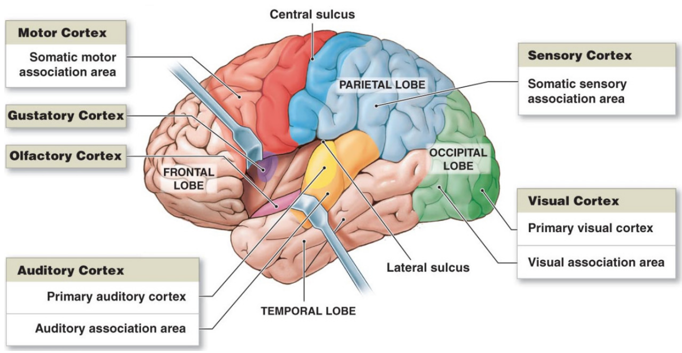


Figure 4.1: The motor and sensory cortices and the associated brain regions [Vanderah and Gould, 2015].

For the scope of this thesis, we shall not go into the details of each brain region mentioned in the figure 4.1. We will only focus on the region that is responsible for providing information regarding the sensorimotor rhythms. According to Nicolas-Alonso and Gomez-Gil [2012], *Motor Cortex* of brain is responsible for carrying the information related to the sensorimotor rhythms.

Motor cortex contains information about imagination of motion.

The reason behind finding out which brain region provides the information regarding the sensorimotor rhythms is to figure out the location from where we need to extract the corresponding neuro-signals. Therefore, to formulate non-invasive BCI, the idea is to place electrodes at the location associated with the motor cortex. This will enable us to extract the neural signals regarding the sensorimotor rhythms.

Location of motor cortex decides the location where the electrodes will be placed.

Here, it is important to first know where to place electrodes to target any specific brain region. For this purpose, we referred to the electrode placement chart provided by Nicolas-Alonso and Gomez-Gil [2012]. Figure 4.2 shows the electrode placement chart covering all the regions of the brain.

Electrode placement chart shows the locations for placing electrodes.

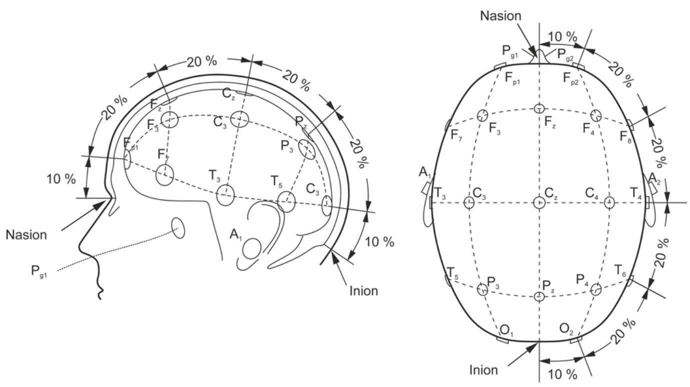


Figure 4.2: The electrode placement locations over various regions of the scalp [Nicolas-Alonso and Gomez-Gil, 2012].

In figure 4.2, we see various circles and a letter associated with each circle. The circles represent locations for electrode placement and each letter corresponds to a specific brain region. Here, the letter **A** represents the ear lobe, **C** the central region, **Pg** the nasopharyngeal, **P** the parietal, **T** the temporal, **F** the frontal and **O** the occipital area [Nicolas-

The circles represent electrode placement locations and the letters represent different brain regions.

Alonso and Gomez-Gil, 2012].

$\mathbf{T_P}$ and $\mathbf{F_P}$ were the desired regions to place electrodes.

Since the idea was to obtain the information regarding the imagination of motion, we targeted areas that covered the motor cortex. Therefore, the intended areas to target were the area between the Temporal and Parietal lobe ($\mathbf{T_P}$) and the area between the Frontal and Parietal lobe ($\mathbf{F_P}$). Figure 4.3 shows $\mathbf{T_P}$ and $\mathbf{F_P}$ as the regions highlighted in red.

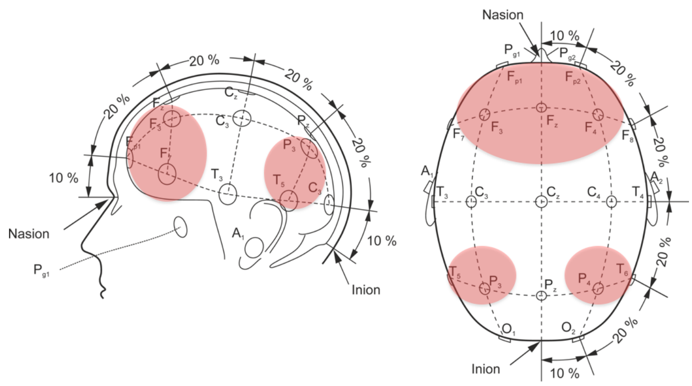


Figure 4.3: Highlighted region represent the areas to target, between the Temporal and Parietal lobe ($\mathbf{T_P}$) and between the Frontal and Parietal lobe ($\mathbf{F_P}$).

Next step was to choose a BCI headband. For that we first needed to decide on a neuroimaging method to use.

Once the regions for the placement of electrodes were determined, the next step was to decide which BCI headband to use in order to extract the required neural signals. But before we could move on to choosing a BCI headband, there was a need to first investigate what neuroimaging method to use. The choice of BCI headband depended on the neuroimaging method we chose.

4.3 Neuroimaging Methods

Let us first define what do we mean by neuroimaging.

Definition: *Neuroimaging*

NEUROIMAGING:
The term neuroimaging refers to the process of producing images of the structure or activity of the brain or other parts of the nervous system [Tan and Nijholt, 2013].

Following are a few neuroimaging methods to acquire neuro-signals from a subject in a non-invasive manner.

- Electroencephalography (**EEG**)
- Magnetoencephalography (**MEG**)
- Functional Magnetic Resonance Imaging (**fMRI**)
- Near Infrared Spectroscopy (**NIRS**)

Table 4.1 shows a summary of the above mentioned non-invasive neuroimaging methods.

Method	Activity Measured	Temporal Resolution	Spatial Resolution	Portability
EEG	Electrical	˜0.05s	˜10mm	Yes
MEG	Magnetic	˜0.05s	˜5mm	No
fMRI	Metabolic	˜1s	˜1mm	No
NIRS	Metabolic	˜1s	˜5mm	Yes

Table 4.1: Summary of neuroimaging methods [Nicolas-Alonso and Gomez-Gil, 2012]

After careful comparison of the above mentioned neuroimaging methods, the most appropriate choice for our research was Electroencephalography (**EEG**). One of the major reasons for choosing EEG was the usability advantages of the EEG signal acquisition process. EEG is non-invasive, easy to use, portable and cost effective method to record neural signals [Abdulkader et al., 2015]. Characteristics wise, EEG signals are noisy and provide low spatial resolution but on the upside, they provide a high temporal resolution [Nicolas-Alonso and Gomez-Gil, 2012].

EEG is non-invasive, easy to use, portable and cost effective. EEG signals are noisy with low spatial resolution but high temporal resolution.

After deciding on the neuroimaging method to be used, we could move on to the next step of choosing a BCI headband that acquired neural signals non-invasively using electroencephalography.

4.4 Neuro-device for Signal Acquisition

We chose the Interaxon MUSE BCI headband.

The choice of the BCI headband depended on its brain region coverage. The choice mainly depended on the electrode placement of the headband. We chose the Interaxon MUSE BCI headband. Interaxon MUSE is a portable and cost effective EEG headband Masood et al. [2016]. Figure 4.4 shows the Interaxon MUSE headband.

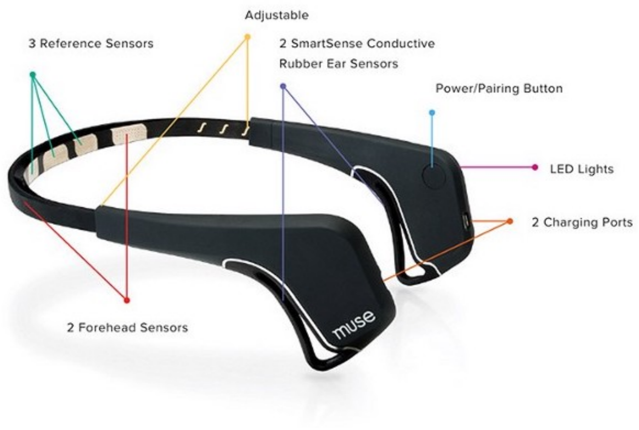


Figure 4.4: Interaxon MUSE BCI headband [Muse, 2015].

Interaxon MUSE BCI headband covers the motor cortex region.

The most important reason for choosing the Interaxon MUSE headband was the fact that it covers the motor cortex region Verlekar et al. [2016]. Figure 4.5 shows the electrode placement chart for the Interaxon MUSE headband.

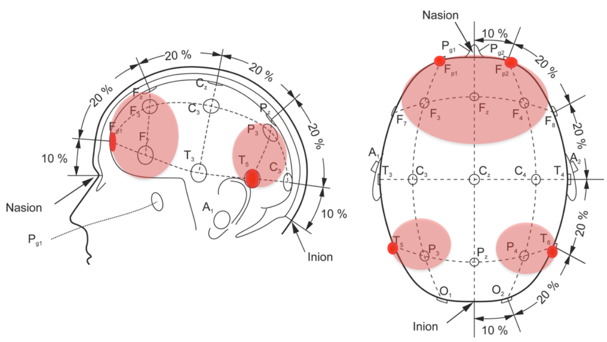


Figure 4.5: Electrode placement (red) of the Interaxon MUSE. Highlighted region represents the areas to target, between the Temporal and Parietal lobe ($\mathbf{T_P}$) and between the Frontal and Parietal lobe ($\mathbf{F_P}$).

In figure 4.5, the electrode locations highlighted in red are the locations of the 4 electrodes of the Interaxon MUSE headband. As shown in the chart, the Interaxon MUSE headband has 2 electrodes in the area between the Temporal and Parietal lobe (**T_P**) and 2 electrodes between the Frontal and Parietal lobe (**F_P**). Because the Interaxon MUSE headband covers the desired brain regions for capturing sensorimotor rhythms, this makes it an appropriate choice.

Interaxon MUSE headband has 2 electrodes each in $\mathbf{T_P}$ and $\mathbf{F_P}$ region.

Once we had decided on what kind of sensory information we required, the device we needed and the neuroimaging method we needed to acquire neural signals to create a non-invasive BCI, we could move on to the next step. The next step was to find out what features of the neural signals did we need to extract.

The next step was to find out what features of the neural signals did we need to extract.

4.5 Features of the Acquired Signals

As mentioned earlier, the information required for our investigation is related to motor imagery. The Beta rhythms β ranging from 12Hz to 30Hz are related to motor activities, more specifically the visualization of motion [Nicolas-Alonso and Gomez-Gil, 2012]. Therefore, we needed to extract the beta rhythms of the acquired neural signals.

Beta Rhythms contain information about motor imagery.

Up till this point, we had gathered all the answers necessary to obtain the desired neural signals from the brain. The next step was to determine which acquired signals are not fit for further usage. For this purpose, we formulated *signal exclusion criteria*.

4.6 Signal Exclusion Criteria

For the purpose of our research, we were very specific about the neural signals we used to train the BCI classifier. In order to minimize the influence of external factors on the acquired signals, we formulated signal exclusion criteria.

According to this criteria, every recorded signal was disregarded if it fell into the following cases:

- Subject had his eyes open during the signal recording process.
- Subject moved any of his body parts during the signal recording process.
- Subject spoke during the signal recording process.
- Subject displaced the BCI headband.
- There was external noise during the recording process.
- Subject had a headache.
- Subject informed that he was distracted.
- Subject informed that he was unable to concentrate.
- Subject informed that he was unable to imagine the given task.
- Subject informed that he was exhausted.
- Subject informed that he was annoyed.

Our next step was to decide on the tools we wanted to use to develop a non-invasive BCI to control a smart home environment.

4.7 Tools Used

The last question to be answered was related to the tools to be used in order to acquire, process and classify the neurosignals.

4.7.1 Headband Callibration

Since the chosen device was the Interaxon MUSE neuro-headband, we used the MUSE Lab application to ensure the accurate calibration of the headband on each subject's head. MUSE Lab application comes with a graphical representation of the calibration status of the headband. It ensures the correct placement of the electrodes and also informs the signal strength received for a specific positioning of the headband. Figure 4.6 shows the device calibration status.

We used MUSE Lab application for BCI headband calibration.

Figure 4.6: Interaxon MUSE device calibration.

Figure 4.6 shows 4 coloured markers, each representing an electrode at a different location. The black circle on top shows that the headband is placed correctly at the centre of the subject's forehead. In case any electrode was misplaced, the corresponding coloured marker would disappear. Similarly, if the device does not receive full signal strength the colour of the corresponding marker is dimmed out. The calibration status shown in figure 4.6 means that all the electrodes are in their correct position and currently, the device is receiving full signal strength.

The 4 coloured markers represent placement of 4 electrodes at different locations.

4.7.2 Signal Acquisition

For the purpose of signal acquisition, along with the Interaxon MUSE headband, we used the MuLes application by BCI Montréal [2015]. MuLes application connects with the BCI headband and logs the acquired brain signals in files with timestamps [Cassani et al., 2015]. Also, MuLes application comes with two additional libraries `mules.py` and `bci_workshop_tools.py`. Using these two libraries made it easy for us to specify the desired features of the acquired neural signals.

We used MuLes application to acquire signals in digital form.

4.7.3 Signal Classification

We used WEKA to classify acquired neuro-signals and to attain level of accuracy of classification.

In order to classify the acquired neuro-signals, we decided to use WEKA [Frank et al., 2009]. It is an open source tool used to apply various machine learning algorithms to any given dataset. WEKA takes the training data in the form of ARFF files. Once the required signals were acquired, they had to be transformed into ARFF files. We did this by writing our own python script. WEKA enables us to view the classification results by simply feeding in a training data file. Much to our benefit, WEKA also lets you define a custom split percentage between training and testing data. Finally, it provides us with the percentage of accuracy of classification based on the given training data.

*

Having made these choices, the next step was to conduct a study to address the research questions of this thesis.

Chapter 5

Let There be Light! - A Preliminary User Study

SUMMARY
This confirmatory study investigated the generalizability of the sensorimotor rhythms generated due to the imagination of any given task to interact with a light.

In this preliminary study, user interviews of 30 participants were conducted to record their neuro-signals against 4 different tasks. Namely, turning on/off a given/imaginary light. Each interview consisted of 3 iterations. The recorded signals of all the tasks were classified using 4 different classifiers i.e. kStar, Random Forest, Multilayer Perceptron and Bayesian Logistic Regression with 66%, 80% and 90% percentage split between training and testing data. The highest level of accuracy achieved was 83.3% using Random Forest. The classification showed the best results when all three iterations were considered collectively. When these iterations were considered separately, the percentage of correctly classified instances dropped as the number of iteration increased.

5.1 Objective

The main objective of this study was to find out the thought process behind performing tasks.

Every action is a result of a thorough thought process. We usually do not feel it because it is either too fast for us to notice or we have developed a habit of doing that action. What we aimed to achieve from this study was to find out how people think if given a specific task to think about. Our goal was to analyse what their thought process is behind performing simple tasks of daily routine e.g. turning on a light. The intent was to find out whether everyone thinks uniquely when given a specific action to interact with an everyday device or not. If these thoughts are not unique, then to what level of accuracy can these thoughts be classified to train a BCI that can enable a user to control a smart home environment.

5.2 Research Question(s)

The scope of this study was limited to one device of everyday use i.e. a light. So, we altered the research questions (cf. Section 1.4 – Research Questions) accordingly for this study.

- What do people think before doing an action related to controlling a light?
- How long does a person take to think about a certain task related to controlling a light?
- When repeatedly thinking about a particular action to control a light, do people think the same every time?
- Is the thought process of different people for a particular action to control a light, unique?

5.3 Variables

This section discusses the various independent and dependent variables of this study.

5.3.1 Independent Variable(s)

Following are the independent variables of this study:

- Tasks to interact with an everyday device i.e. light (cf. Table 5.1)
- Type of light (Given/Imaginary)
- Machine Learning classifiers to classify neural signals (cf. Section 5.7)

5.3.2 Dependent Variable(s)

Following are the dependent variables of this study:

- Sensorimotor EEG signals acquired against each task (cf. Table 5.1)
- Time taken to think about a given task (Window size)
- Percentage of accuracy of classification for each classifier

5.4 Study Setup

The participant was asked to sit on a comfortable seat. In front of him was a table with a table lamp on top. He could sit in any posture he found comfortable. He was asked to wear the Interaxon MUSE device so that we could record his EEG signals while he thought about the given tasks. Figure 5.1 shows the study setup for this study.

Figure 5.1: Study setup for the preliminary study.

5.5 Study Population

30 users (19 males, 11 females) participated in the user study. Selected participants were aged between 20 to 32 (M = 26, SD = 8.48). It was made sure that all participants had no mental disorders and no history of any mental illness.

30 participants (19 males, 11 females) with no prior knowledge of the study and no mental illness took part in the study.

Participants with any prior knowledge of the kind of study being conducted were excluded from the study. This prior knowledge included the knowledge about the study design and/or the tasks being provided to the participants. The reason of exclusion of participants with any prior knowledge was to make sure that the thought process of the participant during the study was not affected by any prior knowledge.

The interviews were completely anonymous. Each participant was assigned a unique identification number. The general participation details, the interview recording and interview notes were saved with respect to the assigned identification number.

The interviews were completely anonymous.

5.6 Data Collection

The data was collected by conducting user interviews. Each user interview lasted for approximately half an hour. There were 3 iterations in each user interview. Each iteration consisted of the same 4 tasks. Section 5.6.1 – Study Tasks discusses these tasks in detail.

Every user interview had 3 iterations with 4 tasks each.

For each given task, the participant was asked to think about performing a specific action. He could take as much time as he needed. The time user took to think about the given action was recorded. The purpose of recording the time was to determine the *window size*.

Thoughts behind each task and time taken to think was recorded.

WINDOW SIZE:
The time any person takes to think about a particular action.

Definition:
Window Size

While the user was thinking about the specified action, his brain signals were recorded and stored against his identification number for further analysis later. Once the user was finished thinking about that action, he was asked to explain it in as much detail as he could. All the user interviews were recorded with the consent of the participant.

User was asked to explain his thoughts after signal recording process.

5.6.1 Study Tasks

The study comprised of the following two sets of tasks.

- The first set of tasks were related to a light of the subject's imagination. This could be any light, at any time of the day and at any location.

- For the second set of tasks, the participant was provided with a specific light i.e. a table lamp. He was informed about how the functions of the lamp worked. Figure 5.2 shows the table lamp provided to the participants for the second set of tasks i.e. L3, L4 in table 5.1.

Figure 5.2: Table lamp used for the preliminary study.

The participants had the freedom to imagine the tasks however they wanted to and to take as much time as they needed.

The participants were asked to think about the following four tasks:

Task Id	Task Description
L1	Turn on any imaginary light
L2	Turn off any imaginary light
L3	Turn on this table lamp
L4	Turn off this table lamp

Table 5.1: Task List of the Preliminary Study

In addition to recording the neuro-signals for these tasks, the participants were also asked to explain exactly what they imagined after every recording.

5.7 Results

Once the signal recording process was finished and the interviews were transcribed, we analysed the acquired data to answer the following questions:

What do people think before doing an action related to controlling a light?

In order to answer this question, the participants were asked to describe their thoughts for every given task. According to the participants' explanation of their thoughts, they imagined the exact steps they planned to perform to do the task at hand. Quoting one of the participants' answer to what he thought in order to turn on the given table lamp:

Users imagined the exact steps they planned to perform to do the task at hand.

> "I was thinking about moving my hand to the switch and pressing the button and then I would see the light. " – **[P13]**

How long does a person take to think about a certain action related to controlling a light?

In order to calculate the window size, the time taken by each participant to imagine a task was recorded. An average of the recorded time durations was considered as the window size to be used in further studies. The window size was calculated to be 3 seconds.

Window size was calculated to be 3 seconds.

When repeatedly thinking about a particular action to control a light, do people think the same every time?

In the study, each participant was asked to think about the same 4 tasks 3 times. Each time, once they were finished

Participants imagined the same thing in every iteration.

thinking about a given action, they explained in detail what they imagined. Upon comparing their answers for all the three iterations, we observed that participants imagined the same thing in every iteration. When asked about the reason, one of the participants reported:

> "Once I have imagined something, it is easy for me to do it again and again. It just comes to me." – **[P27]**

Is the thought process of different people for a particular action to control a light, unique?

Neuro signals were classified to identify their uniqueness.

To answer this question, we relied on the classification results of the recorded neural signals against each task. In order to identify whether the sensorimotor EEG signals against the thoughts to control an everyday device are unique or not, the EEG signals of each participant were recorded and then classified.

Signal Classification

The recorded signals were classified using the following machine learning classifiers:

- Multilayer Perceptron
- Random Forest
- kStar
- Bayesian Logistic Regression

The classification was performed with a percentage split of 66%, 80% and 90% between the training and testing data.

The analysis was performed between the task sets (L1,L2) and (L3,L4) (cf. Table 5.1) for all iterations altogether and also, separately for 1st, 2nd and 3rd iteration.

Classification Results

Table 5.2 shows the level of accuracy achieved by all the tasks using the four classifiers, previously mentioned.

Discussion

Considering the classification results shown in table 5.2, we made the following observations:

- At best, EEG signals recorded against the thoughts to interact with a light, are classifiable up to **66.6%** by the Multilayer Perceptron, **83.3%** by Random Forest, **66.6%** by kStar and **58.8%** by Bayesian Logistic Regression. Although the percentage of accuracy of classification in most cases is close to chance level, it nonetheless shows that the signals acquired against thoughts for controlling a device of everyday use, are not unique.

- The percentage of correctly classified instances decreases as we move from 1st to 3rd iteration. One of the reasons reported by the participants was the exhaustion caused by having to think the same thing again and again.

- The level of accuracy does not show much variation when comparing classification results of signals acquired for the tasks related to a given light and any light of the subject's imagination.

Classification Results													
Task Id	**Iteration**	**Multilayer Perceptron**			**Random Forest**			**kStar**			**Logistic Regression**		
		66%	**80 %**	**90 %**	**66%**	**80 %**	**90 %**	**66%**	**80 %**	**90 %**	**66%**	**80 %**	**90 %**
L1-L2	All	52.5%	45.7%	64.7%	38.9%	48.5%	64.7%	52.5%	51.4%	58.8%	42.3%	57.1%	58.8%
	1st	50%	58.3%	66.6%	45%	33.3%	83.3%	40%	41.6%	66.6%	55%	41.6%	50%
	2nd	45%	33.3%	33.3%	35%	16.6%	33.3%	40%	33.3%	33.3%	40%	33.3%	33.3%
	3rd	27.7%	27.2%	60%	33.3%	0%	20%	16.6%	18.1%	40%	38.8%	45.4%	40%
L3-L4	All	52.3%	54%	61.1%	41.2%	48.6%	38.8%	52.3%	56.7%	55.5%	50.7%	51.3%	55.5%
	1st	50%	46.1%	50%	36.3%	53.8%	16.6%	54.5%	61.5%	50%	54.5%	38.4%	33.3%
	2nd	40.9%	23.0%	50%	36.3%	38.4%	16.6%	31.8%	23%	0%	36.3%	23%	33.3%
	3rd	31.5%	36.3%	50%	26.3%	18.1%	0%	47.3%	27.2%	16.6%	42.1%	36.3%	33.3%
L1 L2 L3 L4	All	47.9%	49.2%	52.7%	52.8%	45%	38.8%	49.5%	49.2%	47.2%	49.5%	46.4%	41.6%

Table 5.2: Classification Results: Level of accuracy achieved by the neuro-signals acquired against the tasks mentioned in Table 5.1.

5.8 Additional Observations

During the entire course of the preliminary study, we made a few additional observations:

- Participants with long hair had problems wearing the BCI headband. The signal strength varied due to the hindrance caused by the hair.
- Participants who wore glasses everyday were more comfortable with using the headband. On the other hand, they had to take off their glasses to wear the BCI headband, which caused inconvenience.

5.9 Qualitative User Feedback

In addition to signal recordings, the participants were also asked a few questions to gather some qualitative feedback regarding various aspects of the intended BCI system. Figure 5.3 shows the results of user responses to the question about whether the users found the Interaxon MUSE headband annoying to wear or not. **80%** of the participants did not find the device annoying to wear.

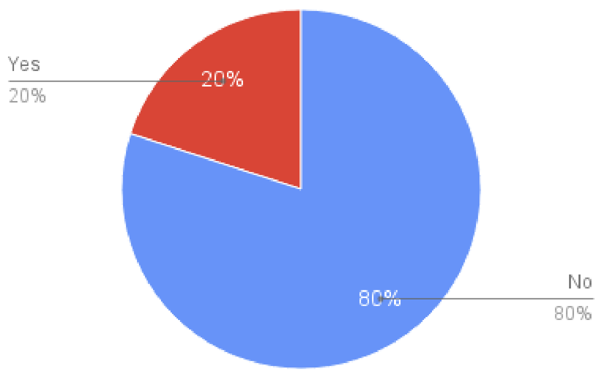


Figure 5.3: User responses to whether they found wearing a BCI headband annoying or not.

The next question was regarding imagining a given task. Figure 5.4 shows the user responses to whether imagining a given task came naturally to them or they had to make an effort to imagine it. **60%** of the participants responded that imagining a given task came naturally to them and they did not have to make an effort.

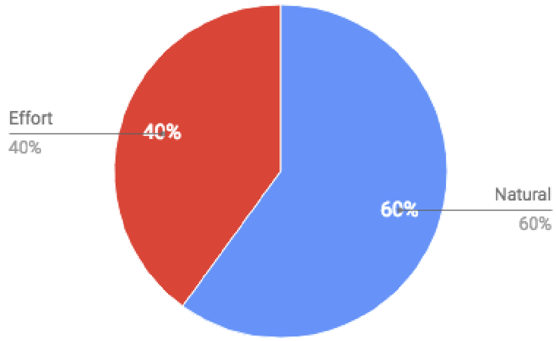


Figure 5.4: User responses to whether imagining a given task came naturally to them or they had to make an effort to imagine it.

The next question was regarding thinking about a given light versus a light of the user's imagination. Figure 5.5 shows the user responses to whether imagining a given light was easier than a light of their imagination or was it the same for both cases. **43.3%** of the participants responded that thinking about a light of their own imagination was easier. Whereas, **30%** of the participants believed that it was equally easy to think about both cases.

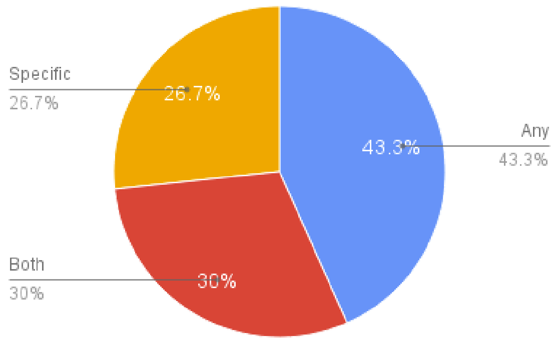


Figure 5.5: User responses to whether imagining a given light was easier than a light of their imagination or was it the same for both cases.

The next question was regarding user preference to use a

BCI to interact with a smart home environment. Figure 5.6 shows the user responses to whether they would want to use a BCI system to interact with a device of everyday use or not. **80%** of the participants responded that they would like to use BCI to control everyday devices.

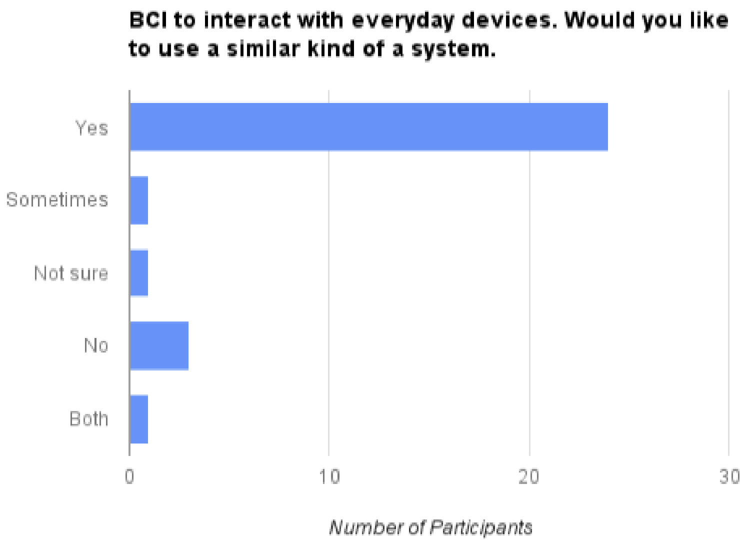


Figure 5.6: User responses to whether they would want to use a BCI system to interact with a device of everyday use or not.

The results of the preliminary study formed the foundation to an extended investigation for various other everyday devices in a smart home environment. In further studies, in addition to expanding the scope of this study by adding tasks related to more everyday device, we made various changes to the study setup in order to minimize external distractions that may have caused a low accuracy level of classification in this preliminary study.

Chapter 6

Subject Independent User Study

SUMMARY

This qualitative study was conducted to investigate how generalizable are the sensorimotor rhythms generated due to the thought process against any particular action to control a smart home environment.

In this user study, the study setup was changed by enclosing the sitting area of the participants with black curtains and by introducing noise cancelling headphones to avoid visual and auditory distractions. The instructions were pre-recorded to ensure consistency. User interviews of 30 participants were conducted to collect their thoughts against 34 different tasks related to interacting with 6 different devices of daily use. Namely, light, fan, TV, AC, door and thermostat. Each interview consisted of 3 iterations. The recorded signals of all the tasks were classified using 3 different classifiers i.e. Multilayer Perceptron, kStar and Random Forest with 80% percentage split between training and testing data. The classification showed a variation of accuracy level from 74.23% to 96.43% for Multilayer Perceptron, 48.47% to 96.29% for kStar and 83.01% to 100% for Random Forest.

In the preliminary study, we investigated how classifiable are thoughts when used as an input to control a light. Based on the results of the preliminary study, we proceeded with conducting another study that extended the scope by including more devices that we use in our daily routine.

6.1 Objective

How well would a Subject-Independent BCI system work to control a smart home environment?

The main objective of this research was to use BCI as means to control a smart home environment. This study contributed into finding out how well would a Subject-Independent BCI perform while interacting with various everyday devices. In order to identify that, we selected 6 different devices of everyday use and asked user to think about certain tasks related to interacting with these devices. The classification results of the acquired signals for these tasks provided the level of accuracy that the system achieved.

6.2 Research Question(s)

As per the results of the preliminary study, we found out that the thought process of different people behind a particular action to control a light is not unique. This study addresses the same question for various devices of everyday use. This study focused on the following research question:

- How classifiable are neuro-signals acquired against the thought process of different people for controlling various devices of everyday use?

6.3 Variables

This section discusses the various independent and dependent variables of this study.

6.3.1 Independent Variable(s)

Following are the independent variables of this study:

1. Devices of everyday use (Light, Fan, AC, TV, Thermostat, Door)
2. Tasks to think about (cf. Table 6.1)
3. Machine learning classifiers (cf. Section 6.8)

6.3.2 Dependent Variable(s)

Following are the dependent variables of this study:

1. Signals acquired against each task
2. Percentage of accuracy of classification

6.4 Study Setup

The user was asked to sit on a comfortable couch surrounded by black curtains. The participant was asked to sit back in a relaxed posture with his eyes closed. The curtains were introduced to avoid any visual distractions that the user might face during the entire course of the study. In order to avoid the auditory distractions, the participant was provided with noise cancelling headphones. All the instructions regarding the study were pre-recorded to ensure consistency of environment. Figure 6.1 shows the study setup used.

Curtains enclosed couch and noise cancelling headphones were introduced to minimize visual and auditory distractions.

Figure 6.1: Study setup of the Subject-Independent study. Participant sitting on the couch enclosed with curtains, wearing the Interaxon MUSE headband and noise cancelling headphones.

6.5 Study Population

30 users (20 males,10 females) participated.

30 users (20 males, 10 females) participated in the study. Selected participants were aged between 21 to 30 (M = 25.5, SD = 6.36). All of the participant had no mental disorders and no history of any mental illness.

Participant with any prior knowledge about the study tasks were excluded.

Participants with any prior knowledge of the kind of study being conducted were excluded from the study. This prior knowledge may include the knowledge about the study design and/or the tasks being provided to the participants.

The reason of exclusion of participants with any prior knowledge was to make sure that the thought process of the participant during the study was not affected by any prior knowledge.

Exclusion of participants was to avoid the impact of their prior knowledge on the study.

The interviews were completely anonymous. Each participant was assigned a unique identification number. The general participant details and interview recordings were saved with respect to the assigned identification number.

Study was completely anonymous.

6.6 Data Collection

In this study, data was acquired by recording the signals against the thought process of controlling various everyday devices in a smart home environment.

Each user interview lasted for approximately 45 minutes with 2 breaks in the middle. There were 3 iterations in each interview. Each iteration consisted of 6 sections with a total of 34 tasks. Each section was related to a specific device of everyday use. The data was collected in an automated manner using a python script. The participant listened to the instructions through the headphones. In each task, the participant was asked to think about performing a specific action to interact with a device of everyday use and he was provided with 3 seconds window to do so (cf. Section 5.7).

Every interview had 3 iterations, each with 6 sections, having 34 tasks in total.

6.7 Study Tasks

Table 6.1 contains the list of tasks each participant was asked to think about.

Device	Task Id	Task Description
AC	A1	Turn on
	A2	Turn off
	A3	Turn up the temperature
	A4	Turn down the temperature
	A5	Make temperature cool
	A6	Make temperature moderate
	A7	Make temperature warm
Door	D1	Open
	D2	Close
Light	L1	Turn on
	L2	Turn off
	L3	Have more light
	L4	Have less light
Fan	F1	Turn on
	F2	Turn off
	F3	Have more fan speed
	F4	Have less fan speed
Television	T1	Turn on
	T2	Turn off
	T3	Turn up the volume
	T4	Turn down the volume
	T5	Change to next channel
	T6	Change to previous channel
	T7	Switch channel to BBC News
	T8	Switch channel to ESPN
	T9	Switch channel to HBO
	T10	Switch channel to CW
Thermostat	TH1	Turn on
	TH2	Turn off
	TH3	Turn up the temperature
	TH4	Turn down the temperature
	TH5	Make temperature cool
	TH6	Make temperature moderate
	TH7	Make temperature warm

Table 6.1: List of tasks related to 6 different devices for the Subject-Independent study.

6.8 Data Classification

The acquired signals against these tasks were classified using the following machine learning classification algorithms:

- Multilayer Perceptron
- kStar
- Random Forest

6.8.1 Classification Results

Table 6.2 shows the level of accuracy achieved by various different combination of tasks. Here, the term *Instances* refers to the number of instances of the training data. Further discussion of the results of this study are in Chapter 8 – Discussion.

Classification Results				
Task Id	**Multilayer Perceptron**	**kStar**	**Random Forest**	**Instances**
A1 A2	92%	85.71 %	92.85 %	140
A3 A4	96.43%	89.28%	96.42%	138
A5 A6 A7	75.61%	73.17%	85.36%	206
A1 A2 A3 A4	83.93%	64.28%	91.07%	278
A1 A2 A3 A4 A5 A6 A7	74.23%	49.48%	87.82%	484
D1 D2	92%	84 %	88%	127
L1 L2	96.15%	96.15%	100%	131
L3 L4	88.89%	92.59%	100%	134
L1 L2 L3 L4	83.01%	64.15%	83.01%	264
F1 F2	88.46%	84.61%	92.30%	132
F3 F4	84.62%	92.30%	88.46%	128
F1 F2 F3 F4	88%	88.46%	88.46%	260
T1 T2	92.59%	92.59%	92.59%	133
T3 T4	92.31%	80.76%	96.15%	132
T5 T6	92.31%	88.46%	92.30%	131
T1 T2 T3 T4	90.56%	73.58%	88.67%	265
T1 T2 T5 T6	86.79%	71.69%	92.45%	264
T1 T2 T3 T4 T5 T6	88.60%	64.55%	96.20%	396
TH1 TH2	96.30%	96.29%	100%	136
TH3 TH4	88.89%	88.88%	92.59%	134
TH5 TH6 TH7	82.50%	75%	87.5%	202
TH1 TH2 TH3 TH4	90.74%	85.18%	92.59%	270
TH1 TH2 TH3 TH4 TH5 TH6 TH7	82.9%	48.47%	85.14%	472
ON/OFF (5 devices)	91.92%	89.25%	93.5132%	672

Table 6.2: Classification results for the Subject-Independent study.

Chapter 7

Subject Dependent User Study

SUMMARY

This qualitative study was conducted for one participant to investigate the accuracy level of a Subject-Dependent BCI system to control a smart home environment.

In this user study, one participant was interviewed to collect his thoughts against 34 different tasks related to interacting with 6 different devices of daily use. Namely, light, fan, TV, AC, door and thermostat. The interview consisted of 20 iterations. The recorded signals of all the tasks were classified using 3 different classifiers i.e. Multilayer Perceptron, kStar and Random Forest with 80% percentage split between training and testing data. The classification results showed a variation of level of accuracy from 64.5% to 97.5% for Multilayer Perceptron, 52.92% to 95.45% for kStar and 71.86% to 100% for Random Forest.

Following the results of the Subject-Independent user study for controlling a smart home environment using BCI, we investigated how well does this system work when trained for a single user. This would make the BCI system subject-dependent. As mentioned earlier, the subject-dependent BCI systems have an additional initial configuration phase, in which the system is trained for a particular user (cf. Section 1.3). This qualitative study was conducted to investigate the level of classifiability of neural signals of a single user, acquired against the thoughts to control a smart home environment.

7.1 Objective

This qualitative study was conducted to investigate the classifiability of the neural signals of a single user, acquired against the thoughts to control a smart home environment.

This study aimed to prove that brain signals acquired from one subject against thoughts to control a smart home environment, are not unique. By recording the signals of one participant against various tasks regarding controlling a smart home environment, we investigated the level of classifiability of these signals. The results of this study lead to answering a vital question of ”To what level of accuracy would a Subject-Dependent BCI work to control a smart home environment?”.

7.2 Intended Use of Study Findings

Comparison of the classifiability of signals for both the Subject-Independent and -Dependent BCI systems for controlling a smart home environment.

The findings of this study were used to compare the accuracy levels of the Subject-Independent and Subject-Dependent BCI systems for controlling a smart home environment. The Subject-Independent BCI has already been investigated to be used as means to control a smart home environment (cf. Chapter 6 – Subject Independent User Study). The results of this study contributed to the comparison of the accuracy levels of two BCI systems with exactly the same study setup and design but only one difference that one system was trained for a particular user and the other system followed the one-size-fits-all approach.

7.3 Research Question(s)

The study focused on the following research question:

- How classifiable are neuro-signals of one subject acquired against the thought process of controlling different devices of everyday use?

7.4 Variables

This section discusses the various independent and dependent variables of this study.

7.4.1 Independent Variable(s)

Following are the independent variables of this study:

1. Devices of everyday use (Light, Fan, AC, TV, Thermostat, Door)
2. Tasks to think about (cf. Table 6.1)
3. Machine learning classifiers (cf. Section 7.7)

7.4.2 Dependent Variable(s)

Following are the dependent variables of this study:

1. Signals acquired against each task
2. Percentage of accuracy of classification

7.4.3 Study Setup

The study setup was an exact replica of the setup used in the Subject-Independent study.

In order to ensure consistency, the study setup was an exact replica of the study setup created for the Subject-Independent study (cf. Section 6.4). This ensured that the change in the study setup did not play a part in influencing user's thoughts. Like in the Subject-Independent study, the participant was seated on a comfortable couch surrounded by black curtains. The curtains were installed to avoid any visual distractions that the user might face during the entire course of the study. In order to avoid the auditory distractions, the participant was provided with noise cancelling headphones. All the instructions regarding the study were pre-recorded to ensure consistency of environment. Figure 6.1 shows the study setup used.

7.4.4 Study Population

1 user (male) participated in the study.

1 user (male) participated in the study. The participant was 28 years of age. He had no mental disorders and no history of any mental illness. He had no prior knowledge of the kind of study that was being conducted. This prior knowledge included the knowledge about the study design and/or the tasks being given to the participant.

7.5 Data Collection

The interview had 20 iterations, each with 6 sections, having 34 tasks in total.

The user interview lasted for approximately 4 hours with 7 breaks in the middle. There were 20 iterations. Each iteration consisted of 6 sections with a total of 34 tasks. Each section was related to a specific device. The data was collected in an automated manner using a python script. The user listened to the instructions through the headphones. In each task, the participant was asked to think about performing a specific action related to controlling a specific device that we use in our daily routine. He was given 3 secs to think about the given task (cf. Section 5.7). While the user thought about the given tasks, his neural signals were recorded using the Interaxon Muse Device and stored for further analysis.

7.6 Study Tasks

Table 6.1 shows the list of tasks provided to the subject related to various different devices of everyday use.

7.7 Data Classification

The acquired signals against all the tasks were classified using the following classifiers:

- Multilayer Perceptron
- kStar
- Random Forest

We used a percentage split of 80% between training and testing data.

7.7.1 Classification Results

Table 7.1 shows the level of accuracy achieved by various different combination of tasks given in table 6.1. Further discussion of the results of this study are in Chapter 8 – Discussion.

Classification Results			
Task Id	**Multilayer Perceptron**	**kStar**	**Random Forest**
A1 A2	95%	92.5%	97.5%
A3 A4	97.5%	92.5%	95%
A5 A6 A7	89.12%	63.59%	88.02%
A1 A2 A3 A4	93.33%	93.33%	100%
A1 A2 A3 A4 A5 A6 A7	78.01%	62.15%	83.56%
D1 D2	95.45%	90.90%	95.45%
L1 L2	93.33%	88.88%	97.77%
L3 L4	95.23%	92.85%	95.23%
L1 L2 L3 L4	83.90%	70.58%	94.25%
F1 F2	88.88%	91.11%	93.33%
F3 F4	95.34%	93.02%	95.34%
F1 F2 F3 F4	94.31%	92.04%	96.59%
T1 T2	95.45%	95.45%	97.72%
T3 T4	95.45%	84.09%	88.63%
T5 T6	93.18%	93.18%	95.45%
T7 T8 T9 T10	64.5%	63.5%	71.86%
T1 T2 T3 T4	93.75%	81.25%	92.5%
T1 T2 T5 T6	89.25%	81.61%	90.8%
T1 T2 T3 T4 T5 T6	90.11%	80.67%	93.04%
TH1 TH2	97.5%	95%	100%
TH3 TH4	92.5%	90%	92.5%
TH5 TH6 TH7	71.66%	60%	76.66%
TH1 TH2 TH3 TH4	87.5%	72.5%	85%
TH1 TH2 TH3 TH4 TH5 TH6 TH7	68.52%	52.92%	87.68%
ON/OFF (5 devices)	96.65%	91.82%	92.41%

Table 7.1: Classification results for the Subject-Dependent study.

Chapter 8

Discussion

Considering the results of both Subject-Independent and Subject-Dependent user studies, we made the following observations:

8.1 Study Setup

Regarding the study setup, we discovered the following:

- Having curtains enclosed study setup helped in minimizing the visual distractions during the study. As one of the participants reported:

  > ″At first, I thought the curtains were a bit strange but I see the point of having them. It kind of helped me in staying focused. I didn't really see anything around so I wasn't thinking about anything other than the given task. It was easy to focus like that. ″ – **[P23]**

- Providing user with noise cancelling headphones with pre-recorded instructions helped in minimizing the auditory distractions during the study. The subject who took part in the Subject-Dependent study stated:

> "The headphones were a good idea, I was only hearing one voice and I knew what to think. Not like I hear a lot of things and have to think really hard to concentrate." – [**P1**]

8.2 Tasks to Control Smart Devices

Considering the results obtained from the Subject-Independent and Subject-Dependent studies, mentioned previously in table 6.2 and table 7.1 respectively, we came across the following findings regarding various smart home devices. Let us go through the findings regarding each device one by one.

8.2.1 Air Conditioner

Regarding the percentage of accuracy achieved for the tasks performed to interact with an air conditioner (AC), we concluded the following:

Turn On/Off

Considering the classification results of two tasks of turning on and off an air conditioner, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**92.85%**) with 140 training instances and Subject-Dependent study (**97.5%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**85.71%**) and Subject-Dependent study (**92.5%**).

Figure 8.1 shows the classification results of turning an AC on/off in the Subject-Independent and Subject-Dependent study.

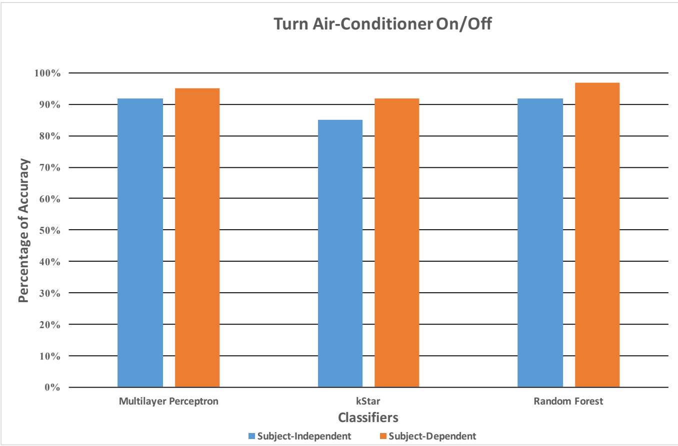


Figure 8.1: Classification results of turning an AC on/off in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **7.14%** error rate as opposed to the **2.5%** error rate obtained by the Subject-Dependent study. Figure 8.2 shows the error rate of turning an AC on/off in the Subject-Independent and Subject-Dependent study.

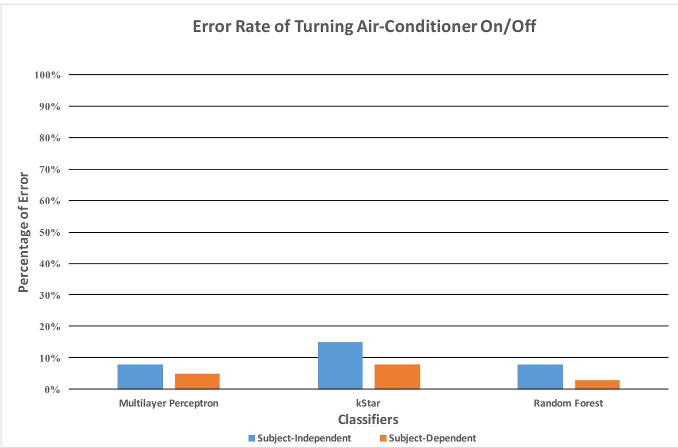


Figure 8.2: Error rate of turning an AC on/off in the Subject-Independent and Subject-Dependent study.

Turn Temperature Up/Down

Considering the classification results of two tasks of turning the temperature one level up or one level down using an air conditioner, we came across the following findings:

- Multilayer Perceptron attained the best level of accuracy for both Subject-Independent study (**96.43%**) with 138 training instances and Subject-Dependent study (**97.5%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**89.28%**) and Subject-Dependent study (**92.5%**).

  Figure 8.3 shows the classification results of turning AC temperature up/down in the Subject-Independent and Subject-Dependent study.

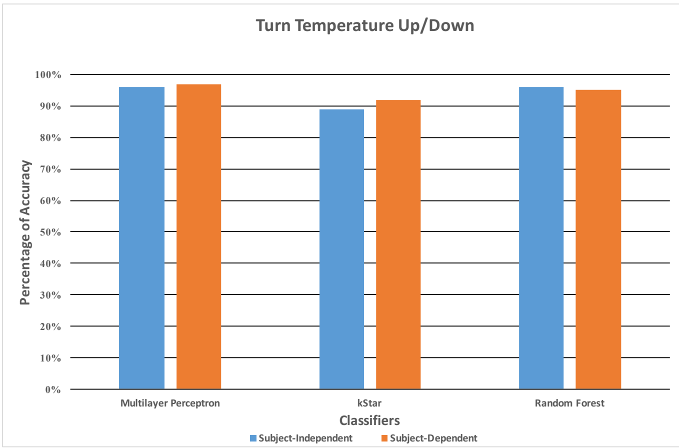


Figure 8.3: Classification results of turning AC temperature up/down in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **3.57%** error rate as opposed to the **2.5%** error rate obtained by the Subject-Dependent study.

Figure 8.4 shows the error rate of turning AC temperature up/down in the Subject-Independent and Subject-Dependent study.

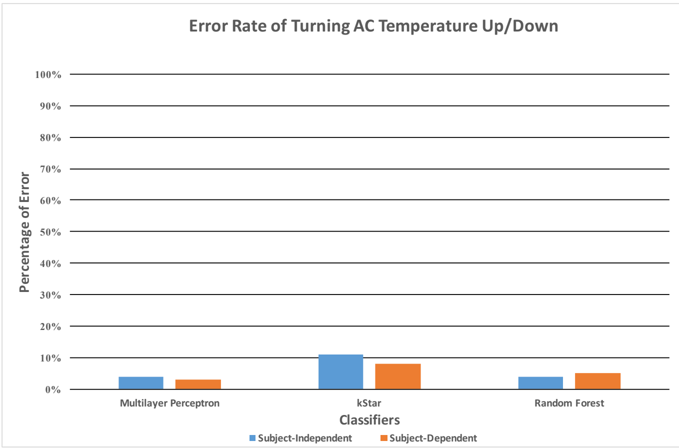


Figure 8.4: Error rate of turning AC temperature up/down in the Subject-Independent and Subject-Dependent study.

Make Temperature Cool/Moderate/Warm

As per the qualitative feedback, it was observed that these tasks were hard to imagine for users. One of the participants of the Subject-Independent study reported:

> "I didn't really know what to think about cool, warm and stuff. I mean, it would have been much simpler if I had a number in mind."
> – **[P8]**

Considering the classification results of three tasks of making the temperature cool, moderate or warm using an air conditioner, we came across the following findings:

- Random Forest attained the best level of accuracy for the Subject-Independent study (**85.36%**) with 206 training instances. The Subject-Dependent study obtained the highest level of accuracy (**89.12%**) using the

Multilayer Perceptron with 20 instances of training data acquired from a single subject.

- kStar attained the least level of accuracy for both Subject-Independent (**73.17%**) and Subject-Dependent study (**63.59%**).

  Figure 8.5 shows the classification results of making AC temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

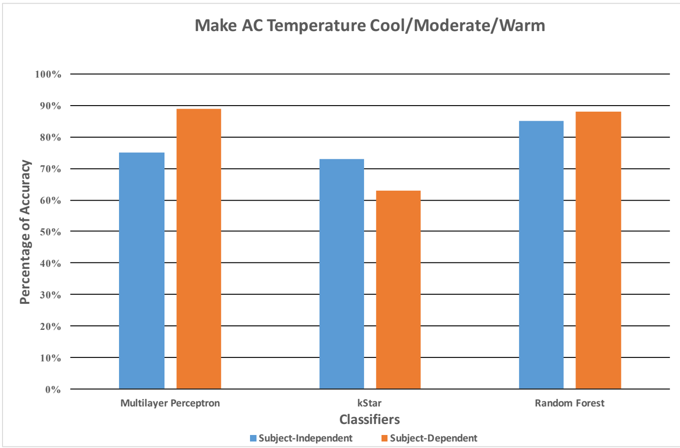


Figure 8.5: Classification results of making AC temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **14.64%** error rate as opposed to the **10.88%** error rate obtained by the Subject-Dependent study.

  Figure 8.6 shows the error rates of making AC temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

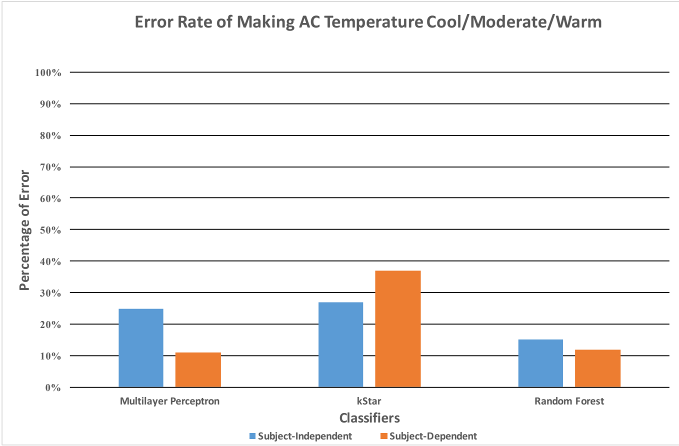


Figure 8.6: Error rates of making AC temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Temperature Up/Down

Considering the classification results of four tasks of turning an air conditioner on or off and turning the temperature one level up or down, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**91.07%**) with 278 training instances and Subject-Dependent study (**100%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**64.28%**) and Subject-Dependent study (**93.33%**). The Multilayer Perceptron attained the same level of accuracy as kStar for the Subject-Dependent study.
- In the best case scenario, the Subject-Independent study produced a **8.93%** error rate as opposed to the **0%** error rate obtained by the Subject-Dependent study.

Figure 8.7 shows the classification results of turning AC on/off and making temperature up/down in the Subject-Independent and Subject-Dependent study.

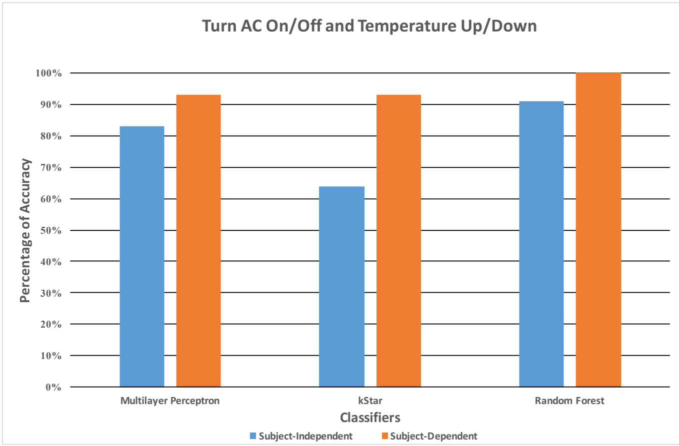


Figure 8.7: Classification results of turning AC on/off and making temperature up/down in the Subject-Independent and Subject-Dependent study.

Figure 8.8 shows the error rates of turning AC on/off and making temperature up/down in the Subject-Independent and Subject-Dependent study.

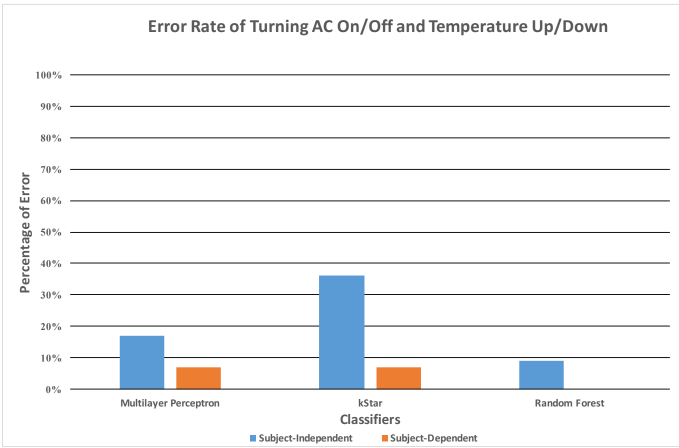


Figure 8.8: Error rates of turning AC on/off and making temperature up/down in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Temperature Up/Down, Cool/Moderate/Warm

Considering the classification results of seven different tasks of turning an air conditioner on or off, turning the temperature one level up or down and making temperature cool, moderate or warm, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**87.62%**) with 484 training instances and Subject-Dependent study (**83.56%**) using 20 instances of training data acquired from a single subject.

- kStar attained the least level of accuracy for both Subject-Independent (**49.48%**) and Subject-Dependent study (**62.15%**).

  Figure 8.9 shows the classification results of turning AC on/off and making temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

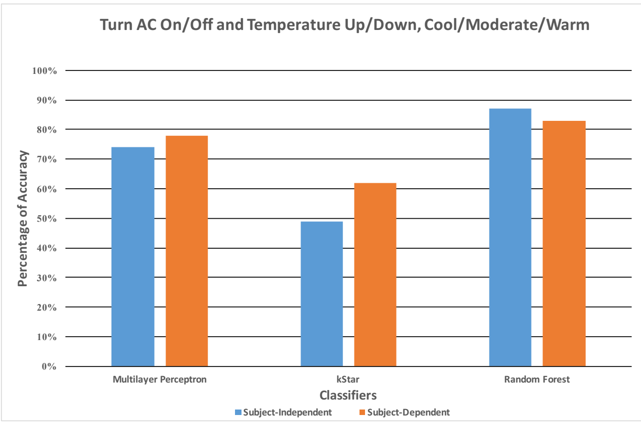


Figure 8.9: Classification results of turning AC on/off and making temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **12.38%** error rate as opposed to the **16.44%** error rate obtained by the Subject-Dependent study. Figure 8.10 shows the error rates of turning AC on/off and making temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

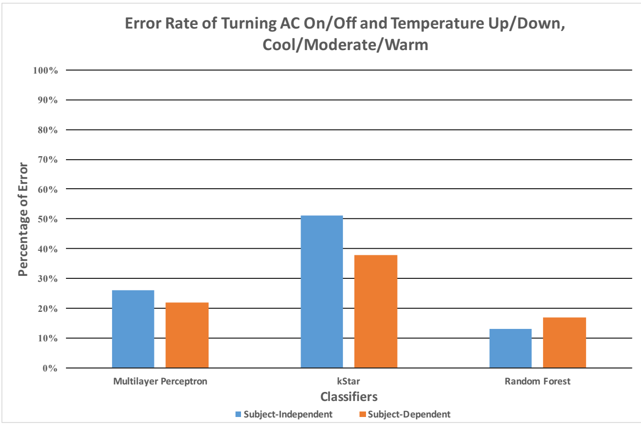


Figure 8.10: Error rates of turning AC on/off and making temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

8.2.2 Door

Regarding the percentage of accuracy achieved for the tasks performed to interact with a door, we concluded the following:

Open/Close

Considering the classification results of two tasks of opening and closing a door, we came across the following findings:

- Multilayer Perceptron attained the best level of accuracy for both Subject-Independent study (**92%**) with 127 training instances and Subject-Dependent study (**95.45%**) using 20 instances of training data acquired from a single subject. However, the Subject-Dependent study obtained the same result using the Random Forest classifier as well.

- kStar attained the least level of accuracy for both Subject-Independent (**84%**) and Subject-Dependent study (**90.60%**).

  Figure 8.11 shows the classification results of opening and closing a door in the Subject-Independent and Subject-Dependent study.

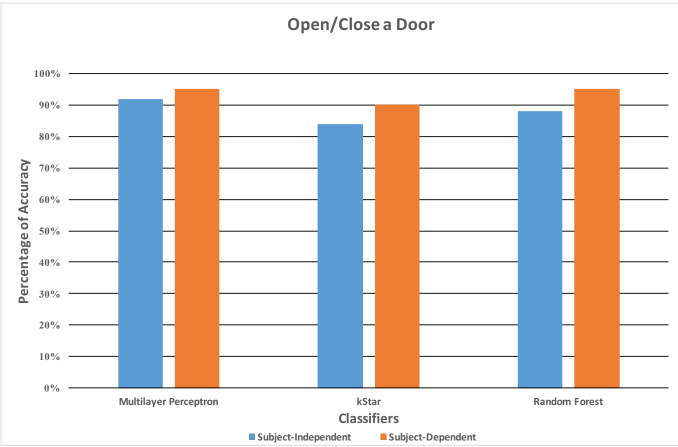


Figure 8.11: Classification results of opening and closing a door in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study has a **8%** error rate as opposed to the **4.55%** error rate obtained by the Subject-Dependent study.

  Figure 8.12 shows the error rates of opening and closing a door in the Subject-Independent and Subject-Dependent study.

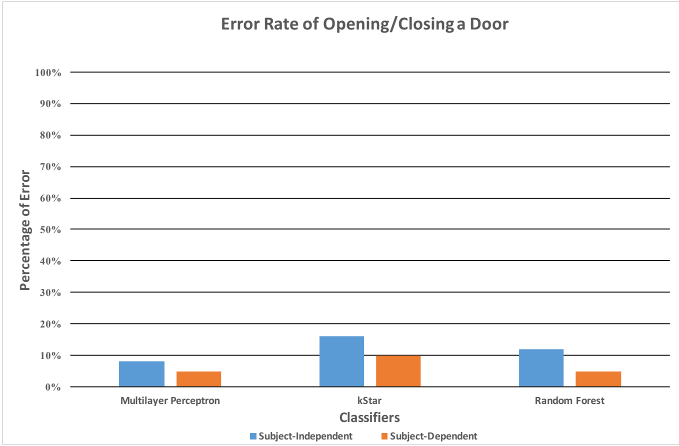


Figure 8.12: Error rates of opening and closing a door in the Subject-Independent and Subject-Dependent study.

8.2.3 Light

Regarding the percentage of accuracy achieved for the tasks performed to interact with a light, we concluded the following:

Turn On/Off

Considering the classification results of two tasks of turning a light on or off, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**100%**) with 131 training instances and Subject-Dependent study (**97.77%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**96.15%**) and Subject-Dependent study (**88.89%**). However, the Multilayer Perceptron obtained the same result as kStar for the Subject-Independent study.

  Figure 8.13 shows the classification results of turning a light on/off in the Subject-Independent and Subject-Dependent study.

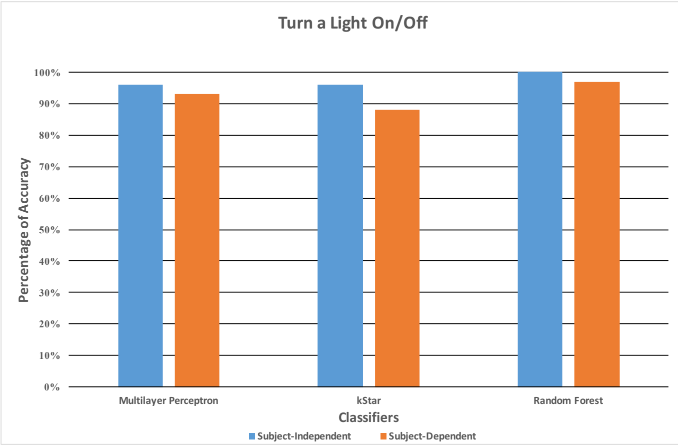


Figure 8.13: Classification results of turning a light on/off in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **0%** error rate as opposed to the **2.23%** error rate obtained by the Subject-Dependent study.

  Figure 8.14 shows the error rates of turning a light on/off in the Subject-Independent and Subject-Dependent study.

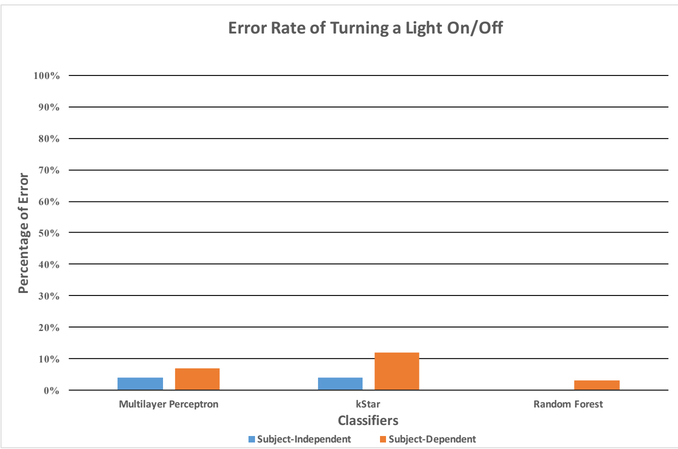


Figure 8.14: Error rates of turning a light on/off in the Subject-Independent and Subject-Dependent study.

Have More/Less Light

Based on the qualitative feedback obtained from the users, it was observed that the tasks of having more/less light were not precise and lead to ambiguity about the scenario the user was supposed to imagine. Quoting one of the participants of the Subject-Independent study:

> ″I wasn′t sure what exactly did it mean by more light. I mean, do I have light and want more light because it′s not enough or I don′t have light and I want light. (It was) a bit confusing. Same for the less one.″ – **[P4]**

Considering the classification results of the two tasks of having more or less light, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**100%**) with 134 training instances and Subject-Dependent study (**95.23%**) using 20 instances of training data acquired from a single subject. However, the Multilayer Perceptron achieved the same level of accuracy as Random Forest for the Subject-Dependent study.
- Multilayer Perceptron attained the least level of accuracy for Subject-Independent study (**88.89%**) and kStar for Subject-Dependent study (**92.85%**).
- In the best case scenario, the Subject-Independent study produced a **0%** error rate as opposed to the **4.77%** error rate obtained by the Subject-Dependent study.

Figure 8.15 shows the classification results of having more/less light in the Subject-Independent and Subject-Dependent study.

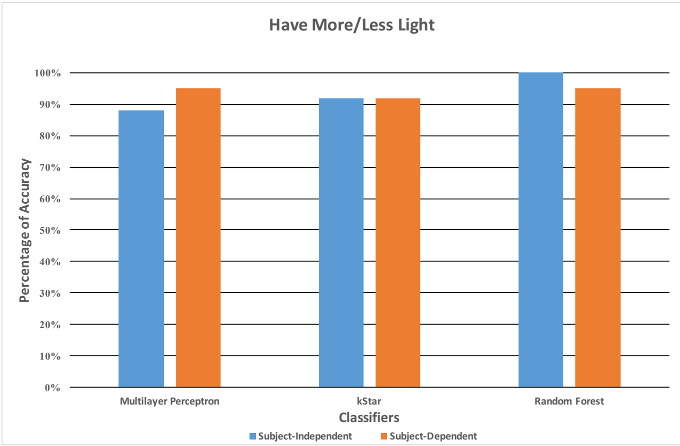


Figure 8.15: Classification results of having more/less light in the Subject-Independent and Subject-Dependent study.

Figure 8.16 shows the error rates of having more/less light in the Subject-Independent and Subject-Dependent study.

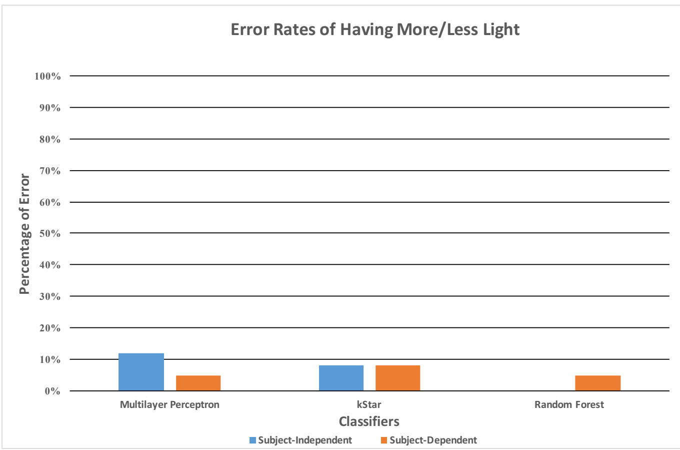


Figure 8.16: Error rates of having more/less light in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Have More/Less Light

Considering the classification results of four tasks of turning a light on or off and having more or less light, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**83.01%**) with 264 training instances and Subject-Dependent study (**94.25%**) using 20 instances of training data acquired from a single subject. However, Multilayer Perceptron achieved the same level of accuracy as Random Forest for the Subject-Independent study.
- kStar attained the least level of accuracy for both Subject-Independent (**64.15%**) and Subject-Dependent study (**70.58%**).

  Figure 8.17 shows the classification results of turning a light on/off and having more/less light in the Subject-Independent and Subject-Dependent study.

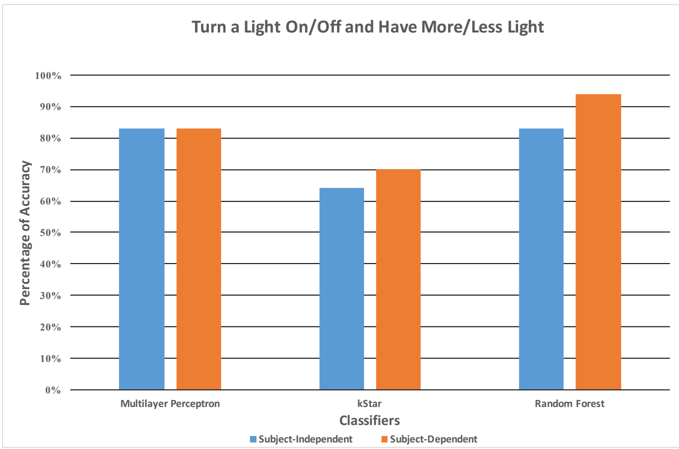


Figure 8.17: Classification results of turning a light on/off and having more/less light in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **16.99%** error rate as opposed to the **5.75%** error rate obtained by the Subject-Dependent study.

Figure 8.18 shows the error rates of turning a light on/off and having more/less light in the Subject-Independent and Subject-Dependent study.

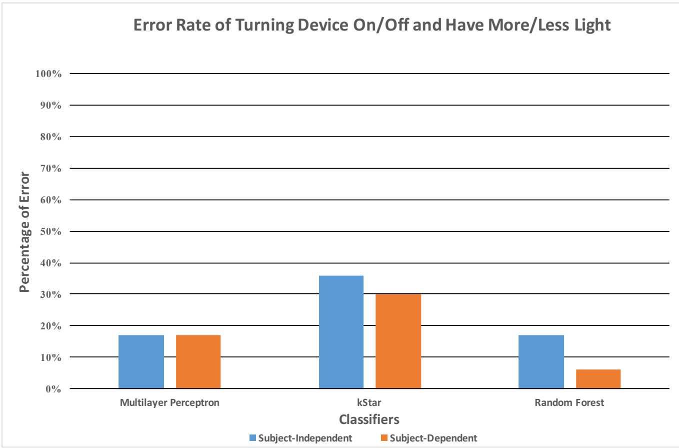


Figure 8.18: Error rates of turning a light on/off and having more/less light in the Subject-Independent and Subject-Dependent study.

8.2.4 Fan

Regarding the percentage of accuracy achieved for the tasks performed to interact with a fan, we concluded the following:

Turn On/Off

Considering the classification results of two tasks of turning a fan on or off, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**92.30%**) with 132 training instances and Subject-Dependent study (**93.33%**) using 20 instances of training data acquired from a single subject.

- kStar attained the least level of accuracy for Subject-Independent study (**84.61%**) and Multilayer Perceptron for the Subject-Dependent study (**88.89%**).

Figure 8.19 shows the classification results of turning a fan on/off in the Subject-Independent and Subject-Dependent study.

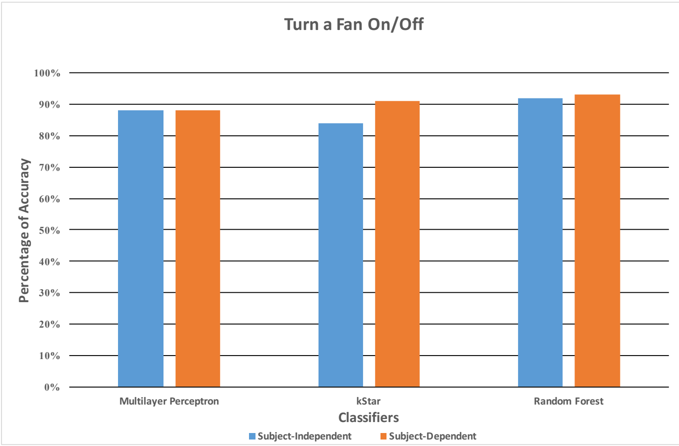


Figure 8.19: Classification results of turning a fan on/off in the Subject-Independent and Subject-Dependent study.

Figure 8.20 shows error rates of turning a fan on/off in the Subject-Independent and Subject-Dependent study.

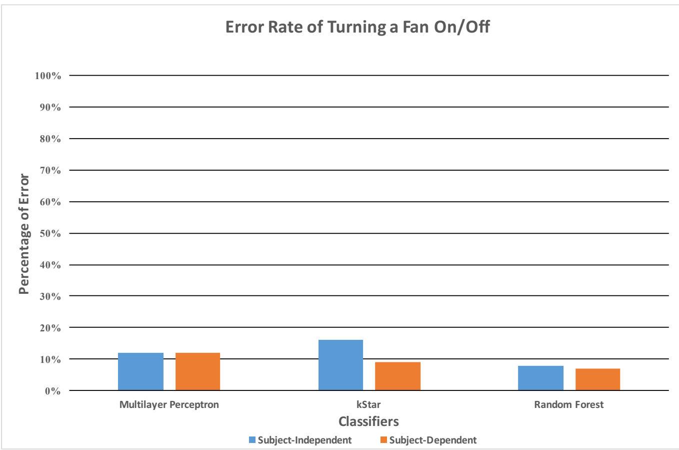


Figure 8.20: Error rates of turning a fan on/off in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **7.7%** error rate as opposed to the **6.67%** error rate obtained by the Subject-Dependent study.

Have More/Less Fan Speed

These two tasks of having more/less fan speed faced similar problems as the tasks of "Having more/less light" (cf. Section 8.2.3). As per the qualitative feedback gathered from the participants of the Subject-Independent user study, these tasks were found ambiguous. Continuing the discussion on having more/less light, the participant reported that:

> "...Same for the fan one. "More" means more, I get it but exactly how much more are we talking about. May be if it was specific it would be simple." – **[P4]**

Considering the classification results of the two tasks of having more or less fan speed, we came across the following findings:

- kStar attained the best level of accuracy for Subject-Independent study (**92.30%**) with 128 training instances. Random Forest and Multilayer Perceptron both obtained the same level of accuracy for the Subject-Dependent study (**95.34%**) using 20 instances of training data acquired from a single subject.
- Multilayer Perceptron attained the least level of accuracy for the Subject-Independent study (**84.62%**) and kStar for the Subject-Dependent study (**93.02%**).
- In the best case scenario, the Subject-Independent study produced a **7.7%** error rate as opposed to the **4.66%** error rate obtained by the Subject-Dependent study.

Figure 8.21 shows the classification results of having more/less fan speed in the Subject-Independent and Subject-Dependent study.

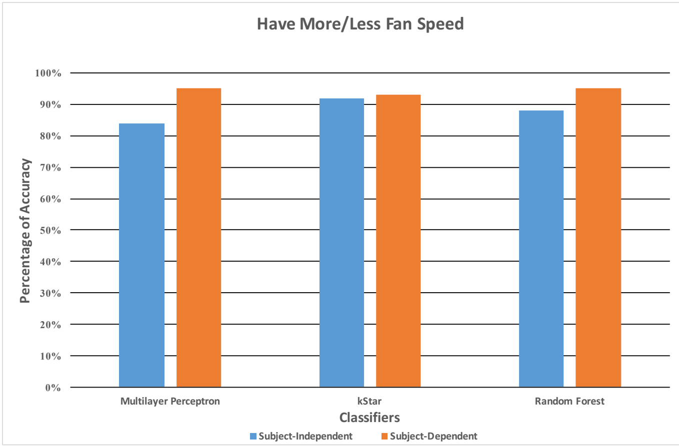


Figure 8.21: Classification results of having more/less fan speed in the Subject-Independent and Subject-Dependent study.

Figure 8.22 shows the error rates of having more/less fan speed in the Subject-Independent and Subject-Dependent study.

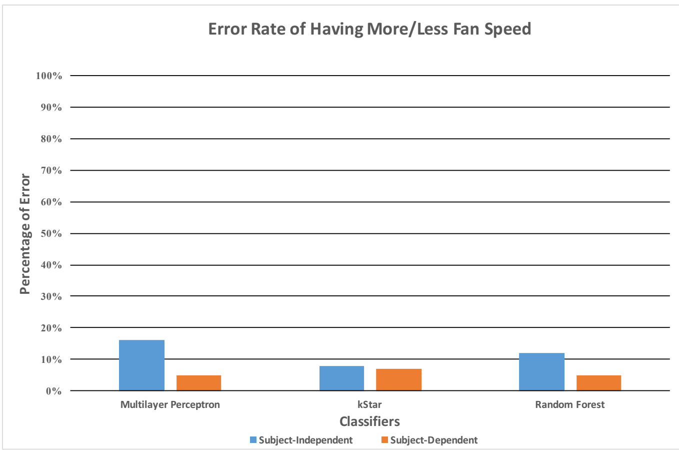


Figure 8.22: Error rates of having more/less fan speed in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Have More/Less Fan Speed

Considering the classification results of the four tasks of turning a fan on or off and having more or less fan speed, we came across the following findings:

- All three classifiers attained approximately the same level of accuracy for Subject-Independent study (**88%**) with 260 training instances. Random Forest obtained the best level of accuracy for the Subject-Dependent study (**96.59%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for the Subject-Dependent study (**92.04%**).

  Figure 8.23 shows the classification results of turning a fan on/off and having more/less fan speed in the Subject-Independent and Subject-Dependent study.

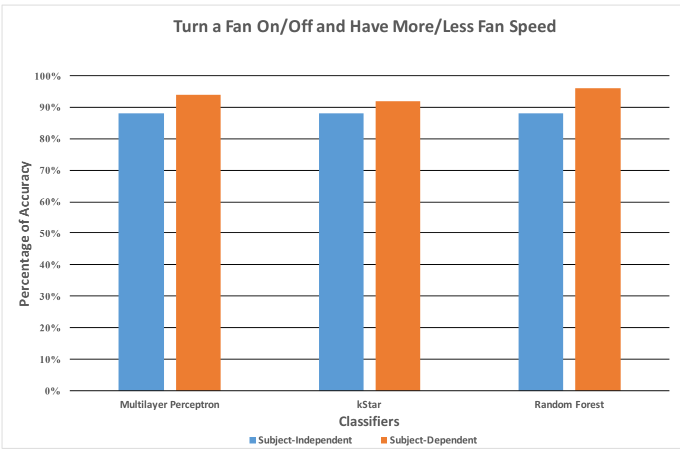


Figure 8.23: Classification results of turning a fan on/off and having more/less fan speed in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **11.54%** error rate as opposed to the **3.41%** error rate obtained by the Subject-Dependent study.

  Figure 8.24 shows the error rates of turning a fan on/off and having more/less fan speed in the

Subject-Independent and Subject-Dependent study.

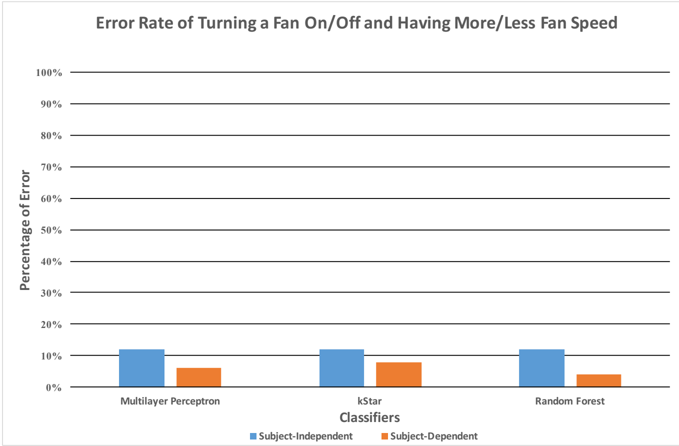


Figure 8.24: Error rates of turning a fan on/off and having more/less fan speed in the Subject-Independent and Subject-Dependent study.

8.2.5 Television

Regarding the percentage of accuracy achieved for the tasks performed to interact with a television, we concluded the following:

Turn On/Off

Considering the classification results of two tasks of turning a television on or off, we came across the following findings:

- All three classifiers obtained the same level of accuracy for the Subject-Independent study (**92.59%**) with 133 training instances. Random Forest performed the best for the Subject-Dependent study (**97.72%**) using 20 instances of training data acquired from a single subject.

- kStar and Multilayer Perceptron attained the same level of accuracy for the Subject-Dependent study (**95.45%**).

Figure 8.25 shows the classification results of turning a TV on/off in the Subject-Independent and Subject-Dependent study.

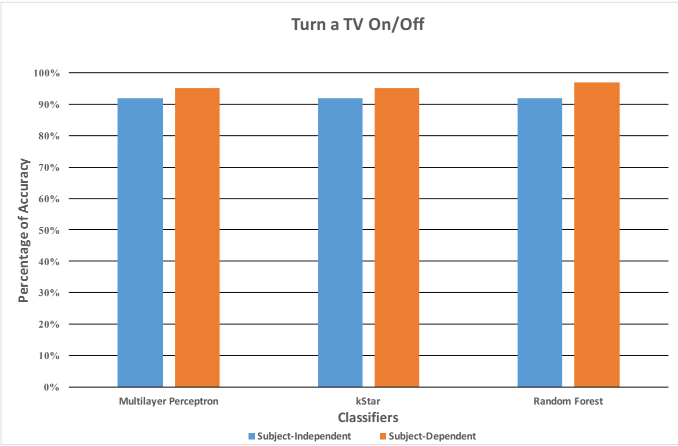


Figure 8.25: Classification results of turning a TV on/off in the Subject-Independent and Subject-Dependent study.

Figure 8.26 shows the error rates of turning a TV on/off in the Subject-Independent and Subject-Dependent study.

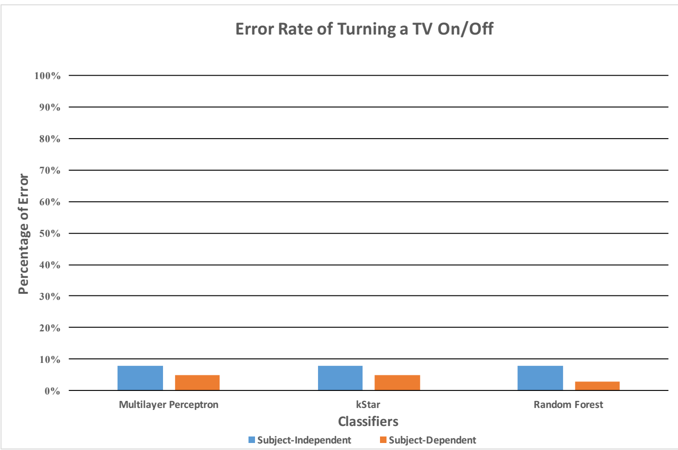


Figure 8.26: Error rates of turning a TV on/off in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **7.41%** error rate as opposed to the **2.28%** error rate obtained by the Subject-Dependent study.

Turn Volume Up/Down

Considering the classification results of two tasks of turning the volume of a television one level up or one level down, we came across the following findings:

- Random Forest attained the highest level of accuracy for the Subject-Independent study (**96.15%**) with 132 training instances. Whereas, the Multilayer Perceptron attained the highest level of accuracy for the Subject-Dependent study (**95.45%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**80.76%**) and Subject-Dependent study (**84.09%**). Figure 8.27 shows the classification results of turning TV volume up/down in the Subject-Independent and Subject-Dependent study.

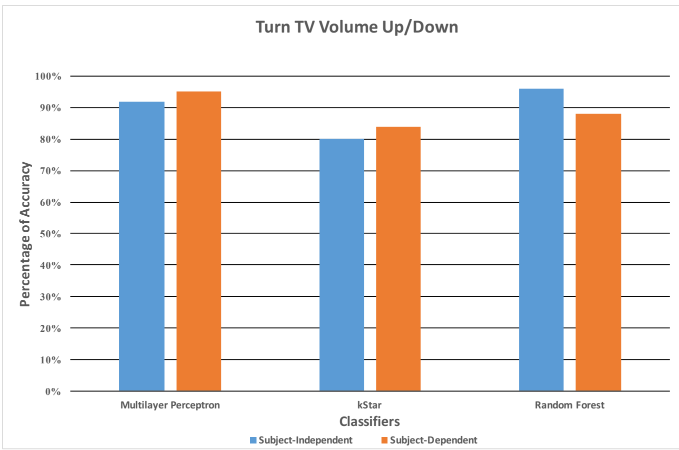


Figure 8.27: Classification results of turning TV volume up/down in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **3.85%** error rate as opposed to the **4.55%** error rate obtained by the Subject-Dependent study.

  Figure 8.28 shows the error rates of turning TV volume up/down in the Subject-Independent and Subject-Dependent study.

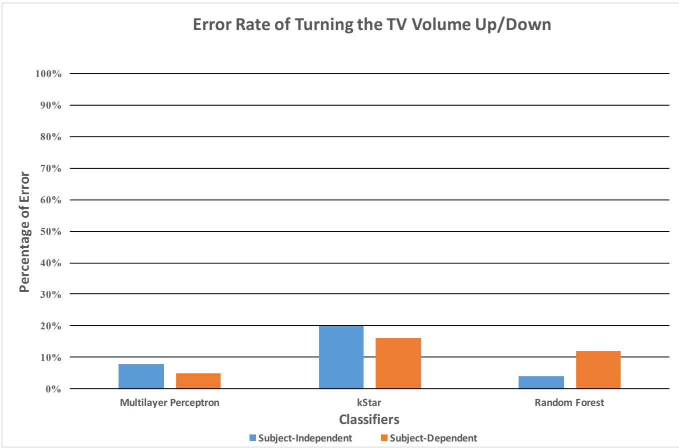


Figure 8.28: Error rates of turning TV volume up/down in the Subject-Independent and Subject-Dependent study.

Change to Next/Previous Channel

Considering the classification results of two tasks of changing the television channel to the next or the previous one, we came across the following findings:

- Multilayer Perceptron and Random Forest attained the same level of accuracy for the Subject-Independent study (**92.31%**) with 131 training instances. On the other hand, Random Forest obtained the highest accuracy level for the Subject-Dependent study (**95.45%**) using 20 instances of training data acquired from a single subject.

- kStar attained the least level of accuracy for both Subject-Independent (**88.46%**) and Subject-

Dependent study (**93.18%**). However, the Multilayer Perceptron reached the same level of accuracy as kStar for the Subject-Dependent study. Figure 8.29 shows the classification results of changing the TV channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

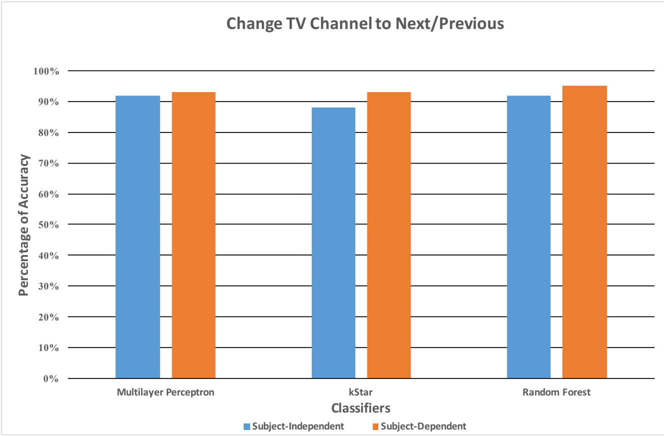


Figure 8.29: Classification results of changing the TV channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

Figure 8.30 shows the error rates of changing the TV channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

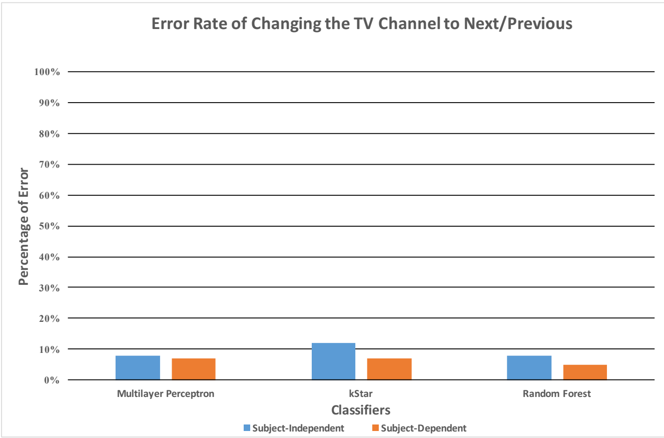


Figure 8.30: Error rates of changing the TV channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **7.69%** error rate as opposed to the **4.55%** error rate obtained by the Subject-Dependent study.

Switch Channel to BBC News/ESPN/HBO/CW

The reason for choosing these four particular TV channels was that according to the Top 12 Most Popular TV Channels Of The World by Wonderslist [2016], the selected channels are the top 4 most popular TV channels watched across the world. There were two main issues faced regarding these tasks:

1. Not every participant was familiar with all of these channels. Quoting one of the subjects of the Subject-Independent study:

   > "I know about BBC News but honestly, I have never watched it. ESPN and HBO are fine but what exactly is CW. I first thought it was Cartoon Network but that would be CN so I wasn't really sure." – **[P17]**

   Another participant reported:

   > "Other than HBO, I don't know any (other channels)." – **[P3]**

2. As per the qualitative feedback obtained from the participants, it was also observed that it was difficult to imagine switching to a specific TV channel if the person does not know what is currently being telecasted there. The observation was same for both the Subject-Independent and Subject-Dependent study. One of the participants reported:

   > "I get it if I have to think of a (channel) number, like 15 for example. But, if I don't know what is playing on HBO then how am I to imagine it? What do I think? Just the name. That was a bit strange." – **[P6]**

Based on these problems, it was observed that the above mentioned tasks were vague and caused ambiguity for the user.

Considering the classification results of switching the TV channel to BBC News, ESPN, HBO or CW, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**88.67%**) with 240 training instances and Subject-Dependent study (**71.86%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**67.92%**) and Subject-Dependent study (**63.5%**).

  Figure 8.31 shows the classification results of switching the TV channel to BBC News/ESPN/HBO/CW in the Subject-Independent and Subject-Dependent study.

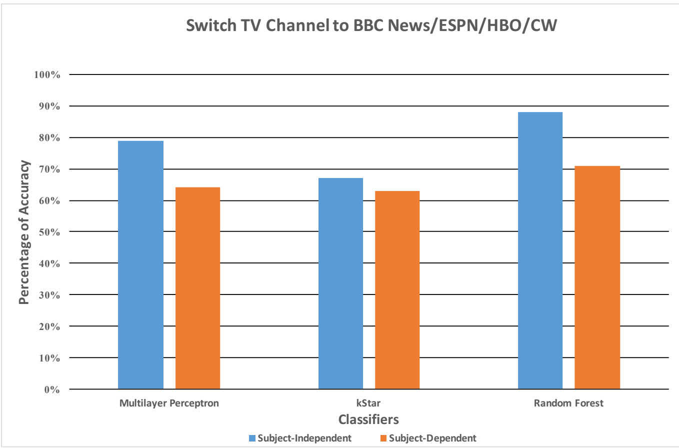


Figure 8.31: Classification results of switching the TV channel to BBC News/ESPN/HBO/CW in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **11.33%** error rate as opposed to the **28.14%** error rate obtained by the Subject-Dependent study.

Figure 8.32 shows the error rates of switching the TV channel to BBC News/ESPN/HBO/CW in the Subject-Independent and Subject-Dependent study.

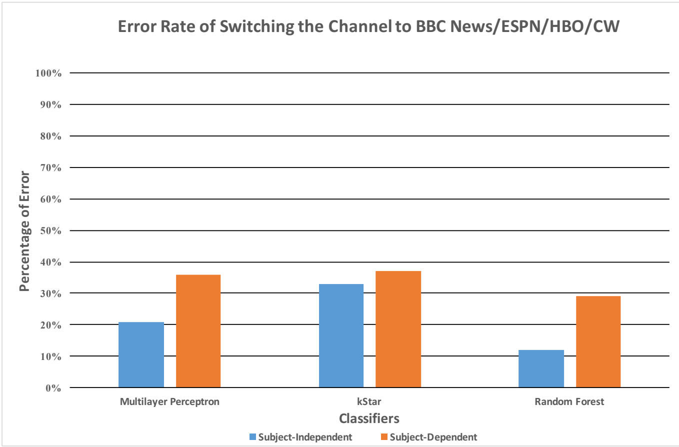


Figure 8.32: Error rates of switching the TV channel to BBC News/ESPN/HBO/CW in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Turn Volume Up/Down

Considering the classification results of four tasks of turning a television on or off and turning its volume one level up or one level down, we came across the following findings:

- Multilayer Perceptron attained the best level of accuracy for both Subject-Independent study (**90.56%**) with 265 training instances and Subject-Dependent study (**93.75%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**73.58%**) and Subject-Dependent study (**81.25%**).

  Figure 8.33 shows the classification results of turning a TV on/off and turning its volume up/down in the Subject-Independent and Subject-Dependent study.

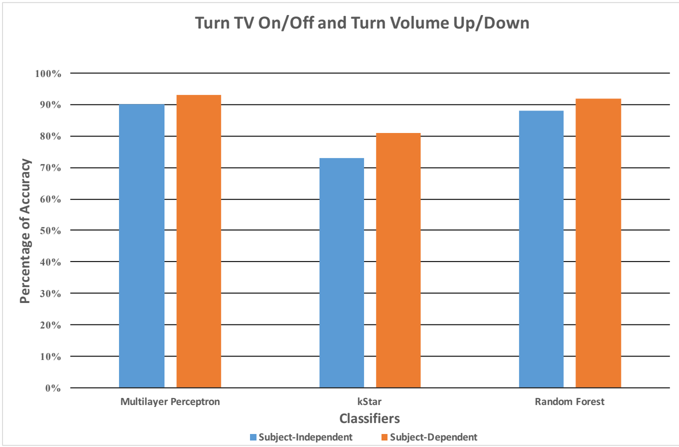


Figure 8.33: Classification results of turning a TV on/off and turning its volume up/down in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **9.44%** error rate as opposed to the **6.25%** error rate obtained by the Subject-Dependent study.

  Figure 8.34 shows the error rates of turning a TV on/off and turning its volume up/down in the Subject-Independent and Subject-Dependent study.

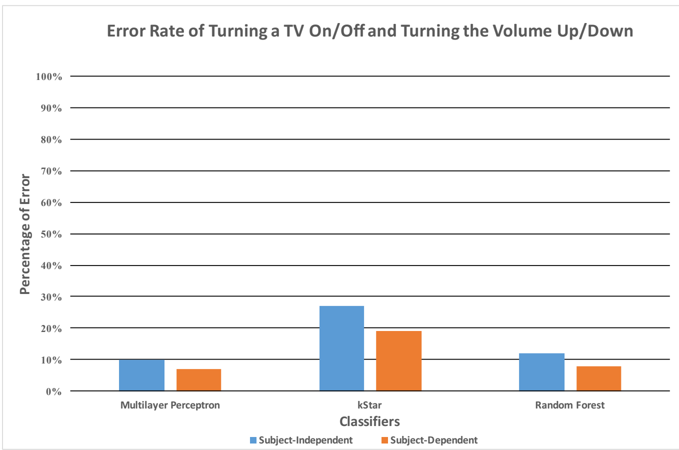


Figure 8.34: Error rates of turning a TV on/off and turning its volume up/down in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Change to Next/Previous Channel

Considering the classification results of four tasks of turning a television on or off and changing the channel to the one next or previous, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**92.45%**) with 264 training instances and Subject-Dependent study (**90.8%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**71.69%**) and Subject-Dependent study (**81.61%**).

  Figure 8.35 shows the classification results of turning a TV on/off and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

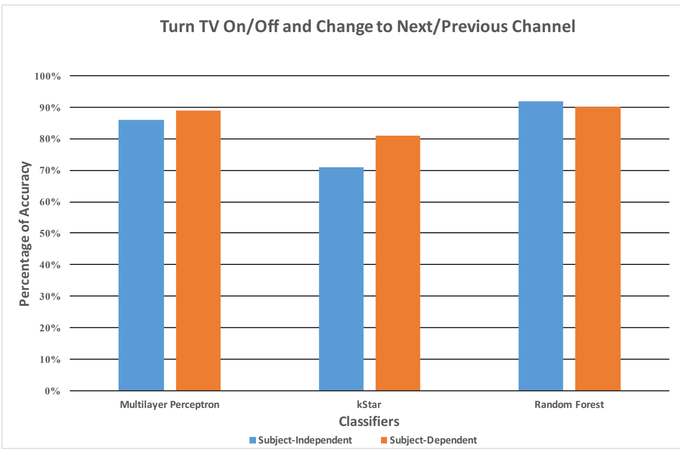


Figure 8.35: Classification results of turning a TV on/off and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **7.55%** error rate as opposed to the **9.2%** error rate obtained by the Subject-Dependent study.

Figure 8.36 shows the error rates of turning a TV on/off and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

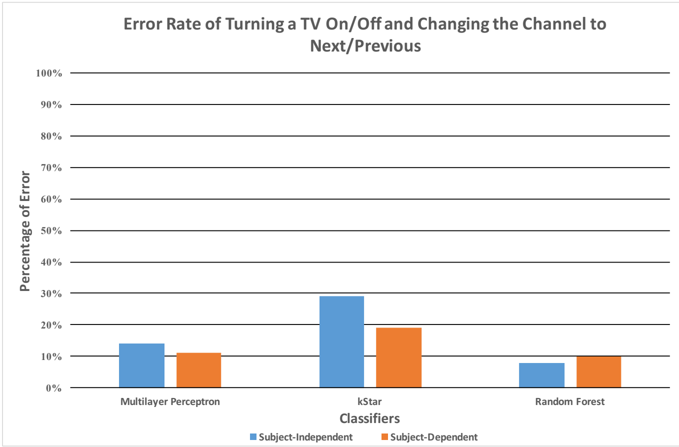


Figure 8.36: Error rates of turning a TV on/off and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off, Turn Volume Up/Down and Change to Next/Previous Channel

Considering the classification results of six tasks of turning a television on or off, turning its volume one level up or down and changing the channel to the one next or previous, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**96.20%**) with 396 training instances and Subject-Dependent study (**93.043%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**64.55%**) and Subject-Dependent study (**80.67%**).

  Figure 8.37 shows the classification results of turning a TV on/off, turning its volume up/down and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

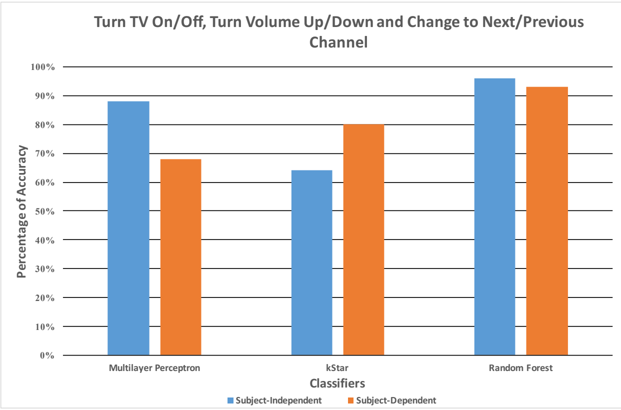


Figure 8.37: Classification results of turning a TV on/off, turning its volume up/down and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

Figure 8.38 shows the error rates of turning a TV on/off, turning its volume up/down and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

Figure 8.38: Error rates of turning a TV on/off, turning its volume up/down and changing the channel to the next/previous one in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **3.8%** error rate as opposed to the

6.95% error rate obtained by the Subject-Dependent study.

8.2.6 Thermostat

One of the issues faced during the recording process for the tasks related to the thermostat was the fact that participants reported that it was difficult to imagine a thermostat. Quoting one of the participants of the Subject-Independent study:

> "What is a thermostat? I wasn't sure. Isn't it the round knob attached to the radiator. I wasn't sure what to think about it." – [**P27**]

Regarding the percentage of accuracy achieved for the tasks performed to interact with a television, we concluded the following:

Turn On/Off

Considering the classification results of two tasks of turning the thermostat on or off, we came across the following findings:

- Random Forest attained the **100%** level of accuracy for both Subject-Independent study with 136 training instances and Subject-Dependent study using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**96.29%**) and Subject-Dependent study (**95%**). However, Multilayer Perceptron obtained the same result as kStar for the Subject-Independent study.
- In the best case scenario, both the studies produced **0%** error rate.

Figure 8.39 shows the classification results of turning the thermostat on/off in the Subject-Independent and Subject-Dependent study.

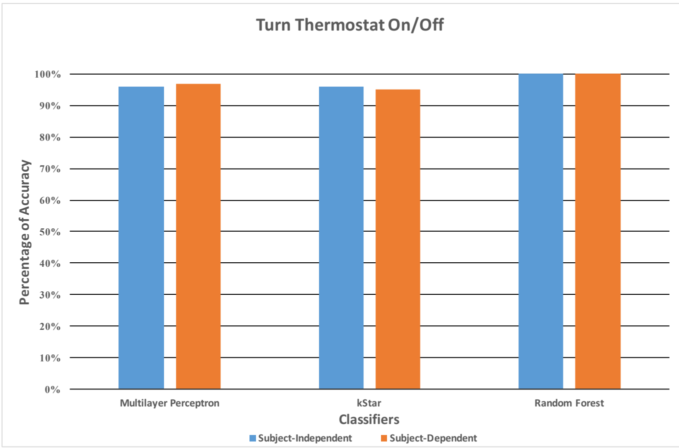


Figure 8.39: Classification results of turning the thermostat on/off in the Subject-Independent and Subject-Dependent study.

Figure 8.40 shows the error rates of turning the thermostat on/off in the Subject-Independent and Subject-Dependent study.

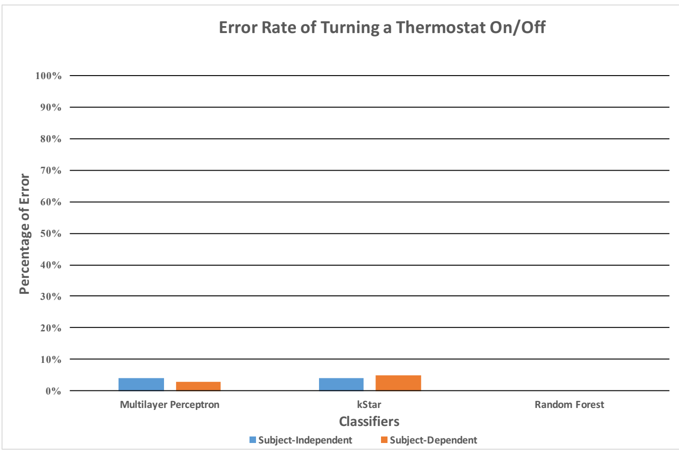


Figure 8.40: Error rates of turning the thermostat on/off in the Subject-Independent and Subject-Dependent study.

Turn Temperature Up/Down

Considering the classification results of two tasks of turning the temperature one level up and down using the thermostat, we came across the following findings:

- Random Forest obtained the highest level of accuracy for the Subject-Independent study (**92.59%**) with 134 training instances. Multilayer Perceptron and Random Forest attained the same level of accuracy for Subject-Dependent study (**92.5%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**88.89%**) and Subject-Dependent study (**90%**). However, Multilayer Perceptron reached the same level of accuracy as kStar for the Subject-Independent study.

  Figure 8.41 shows the classification results of turning the thermostat temperature up/down in the Subject-Independent and Subject-Dependent study.

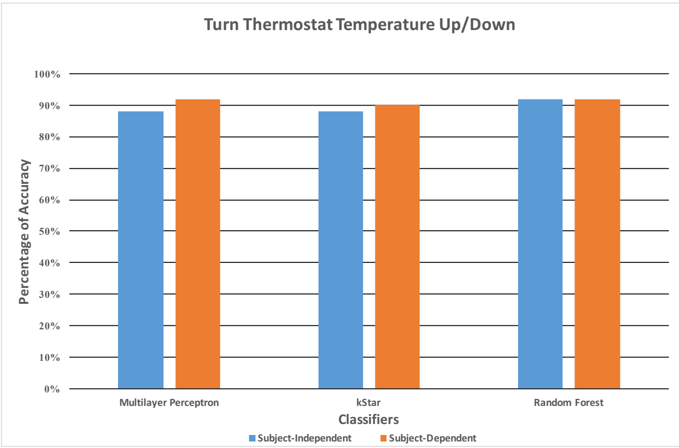


Figure 8.41: Classification results of turning the thermostat temperature up/down in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **7.41%** error rate as opposed to the **7.5%** error rate obtained by the Subject-Dependent study.

Figure 8.42 shows the error rates of turning the thermostat temperature up/down in the Subject-Independent and Subject-Dependent study.

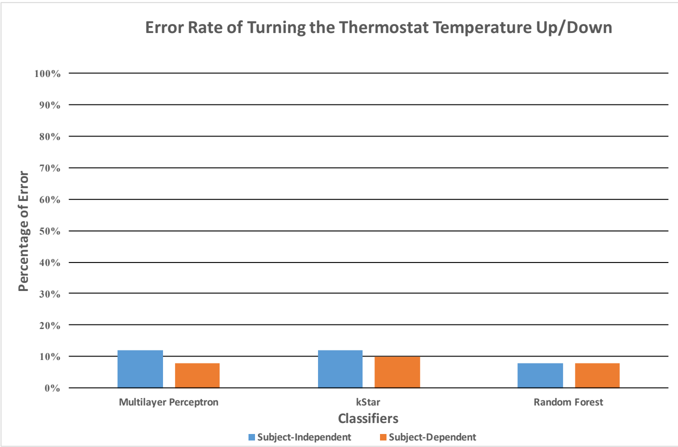


Figure 8.42: Error rates of turning the thermostat temperature up/down in the Subject-Independent and Subject-Dependent study.

8.2.7 Make Temperature Cool/Moderate/Warm

As per the qualitative feedback, it was observed that these tasks were not concretely defined and caused ambiguity for the users. The issue with these tasks was similar to the problem mentioned earlier regarding making the temperature cool, moderate or warm using an air conditioner (cf. Section 8.2.1).

Continuing the feedback regarding the tasks of making the temperature cool, moderate or warm using an air conditioner, one subject reported:

> "I didn't really know what to think about cool, warm and stuff. I mean, it would have been much simpler if I had a number in mind. Same for the thermostat, how cool is cool? I don't know." – **[P8]**

Considering the classification results of three tasks of making the temperature cool, moderate or warm using a thermostat, we came across the following findings:

- Random Forest attained the highest level of accuracy for both Subject-Independent study (**87.5%**) with 202 training instances and Subject-Dependent study (**76.67%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**75%**) and Subject-Dependent study (**60%**).

  Figure 8.43 shows the classification results of making the thermostat temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

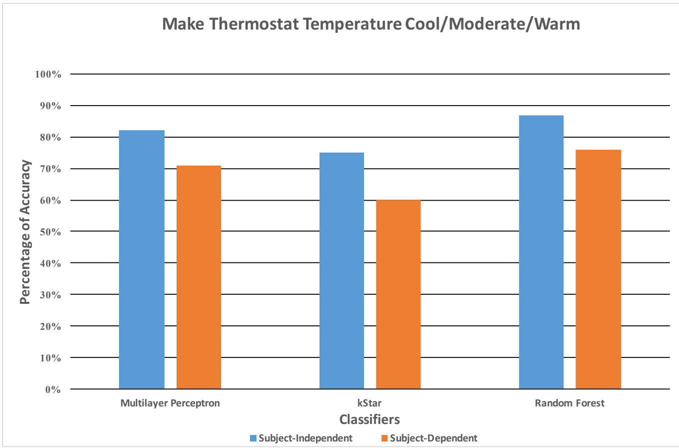


Figure 8.43: Classification results of making the thermostat temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **12.5%** error rate as opposed to the **23.34%** error rate obtained by the Subject-Dependent study.

  Figure 8.44 shows the error rates of making the thermostat temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

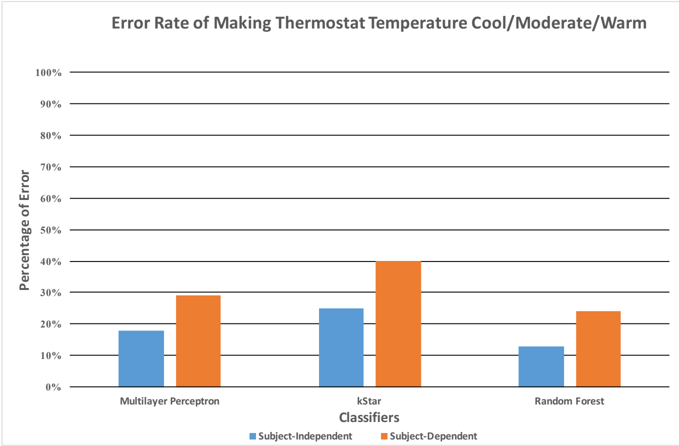


Figure 8.44: Error rates of making the thermostat temperature cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Temperature Up/Down

Considering the classification results of four tasks of turning the thermostat on or off and turning its temperature one level up and down, we came across the following findings:

- Random Forest attained the highest level of accuracy for the Subject-Independent study (**92.59%**) with 270 training instances. Whereas, the Multilayer Perceptron achieved the best results for the Subject-Dependent study (**87.5%**) using 20 instances of training data acquired from a single subject.

- kStar attained the least level of accuracy for both Subject-Independent (**85.18%**) and Subject-Dependent study (**72.5%**).

  Figure 8.45 shows the classification results of turning the thermostat on/off and turning its temperature up/down in the Subject-Independent and Subject-Dependent study.

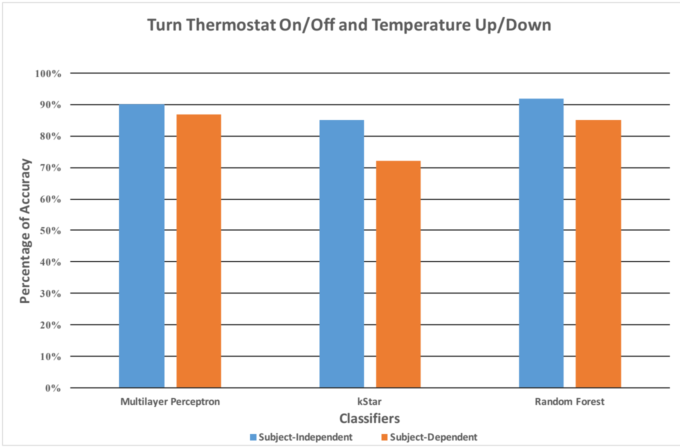


Figure 8.45: Classification results of turning the thermostat on/off and turning its temperature up/down in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **7.41%** error rate as opposed to the **12.5%** error rate obtained by the Subject-Dependent study.

  Figure 8.46 shows the error rates of turning the thermostat on/off and turning its temperature up/down in the Subject-Independent and Subject-Dependent study.

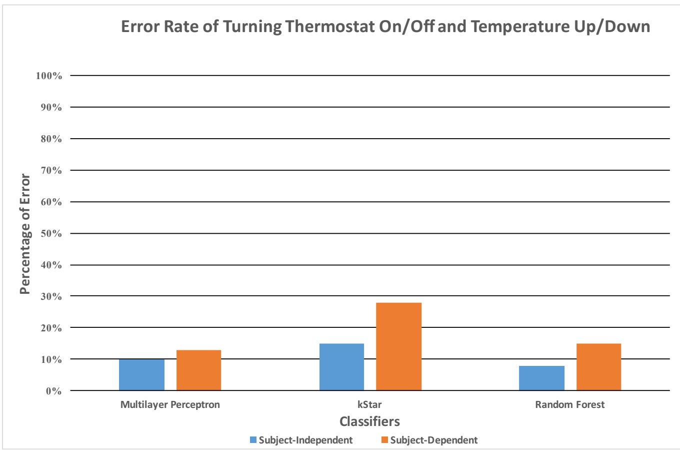


Figure 8.46: Error rates of turning the thermostat on/off and turning its temperature up/down in the Subject-Independent and Subject-Dependent study.

Turn Device On/Off and Temperature Up/Down, Cool/Moderate/Warm

Considering the classification results of seven tasks of turning the thermostat on or off, turning its temperature one level up or down, making it cool, moderate or warm, we came across the following findings:

- Random Forest attained the best level of accuracy for both Subject-Independent study (**85.14%**) with 472 training instances and Subject-Dependent study (**87.68%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**48.47%**) and Subject-Dependent study **(52.92%)**.

  Figure 8.47 shows the classification results of turning the thermostat on/off and turning its temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

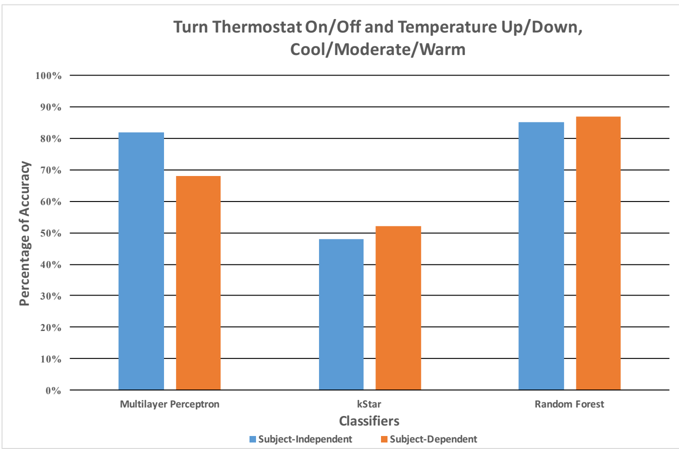


Figure 8.47: Classification results of turning the thermostat on/off and turning its temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

- In the best case scenario, the Subject-Independent study produced a **14.86%** error rate as opposed to the

12.32% error rate obtained by the Subject-Dependent study.

Figure 8.48 shows the error rates of turning the thermostat on/off and turning its temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

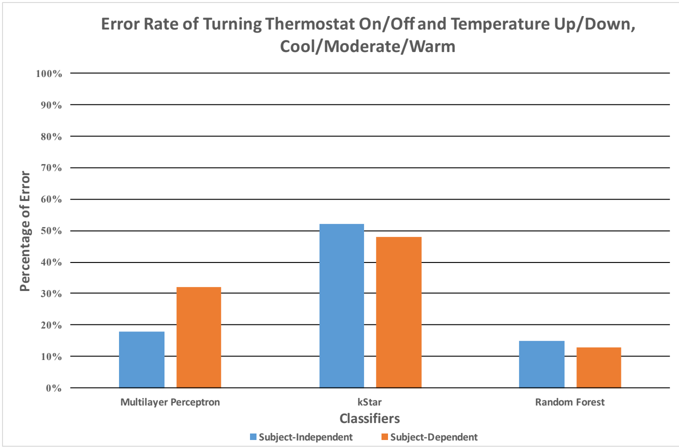


Figure 8.48: Error rates of turning the thermostat on/off and turning its temperature up/down, cool/moderate/warm in the Subject-Independent and Subject-Dependent study.

8.2.8 On/Off 5 Devices

As per the qualitative feedback, it was observed that the tasks such as "turning a specific device on or off" were easier to imagine for subjects. Quoting one of the participants of the Subject-Independent study:

> "I liked the on off tasks. They were the easiest. I could just imagine it, easy and simple." – **[P28]**

As per the classification results of the tasks related to switching on/off 5 different devices i.e. light, fan, television, air conditioner and thermostat, we came across the following findings:

- Random Forest obtained the best level of accuracy for the Subject-Independent study (**93.51%**) with 672 training instances. Whereas, Multilayer Perceptron produced the best results for the Subject-Dependent study (**96.65%**) using 20 instances of training data acquired from a single subject.
- kStar attained the least level of accuracy for both Subject-Independent (**89.25%**) and Subject-Dependent study (**91.82%**).
- In the best case scenario, the Subject-Independent study produced a **6.49%** error rate as opposed to the **3.35%** error rate obtained by the Subject-Dependent study.

Figure 8.49 shows the level of accuracy of On/Off commands of 5 devices in the the Subject-Independent and Subject-Dependent study.

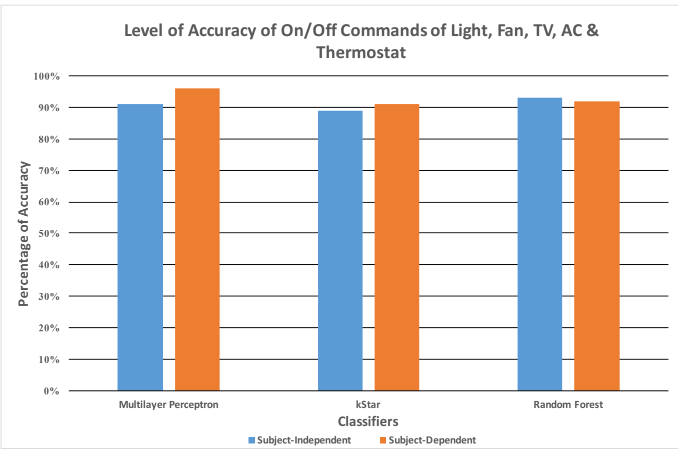


Figure 8.49: Classification results of On/Off commands of light, fan, television, air conditioner and thermostat in the Subject-Independent and Subject-Dependent study.

Figure 8.50 shows the error rates of On/Off commands of 5 devices in the the Subject-Independent and Subject-Dependent study.

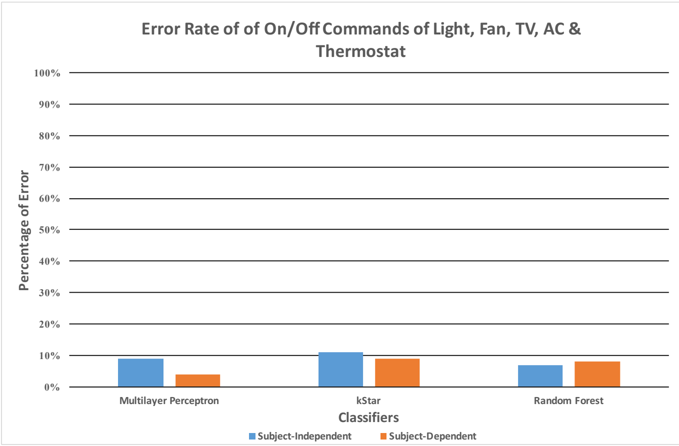


Figure 8.50: Error rates of On/Off commands of light, fan, television, air conditioner and thermostat in the Subject-Independent and Subject-Dependent study.

8.3 At a Glance

This section discusses the level of accuracy and error rate obtained for all the tasks (cf. Table 6.1) in both Subject-Independent and Subject-Dependent study.

8.3.1 Subject-Independent study

Figure 8.51 and figure 8.52 show the accuracy level and error rates respectively, in the Subject-Independent study.

8.3.2 Subject-Dependent study

Figure 8.53 and figure 8.54 show the accuracy level and error rates respectively, in the Subject-Dependent study.

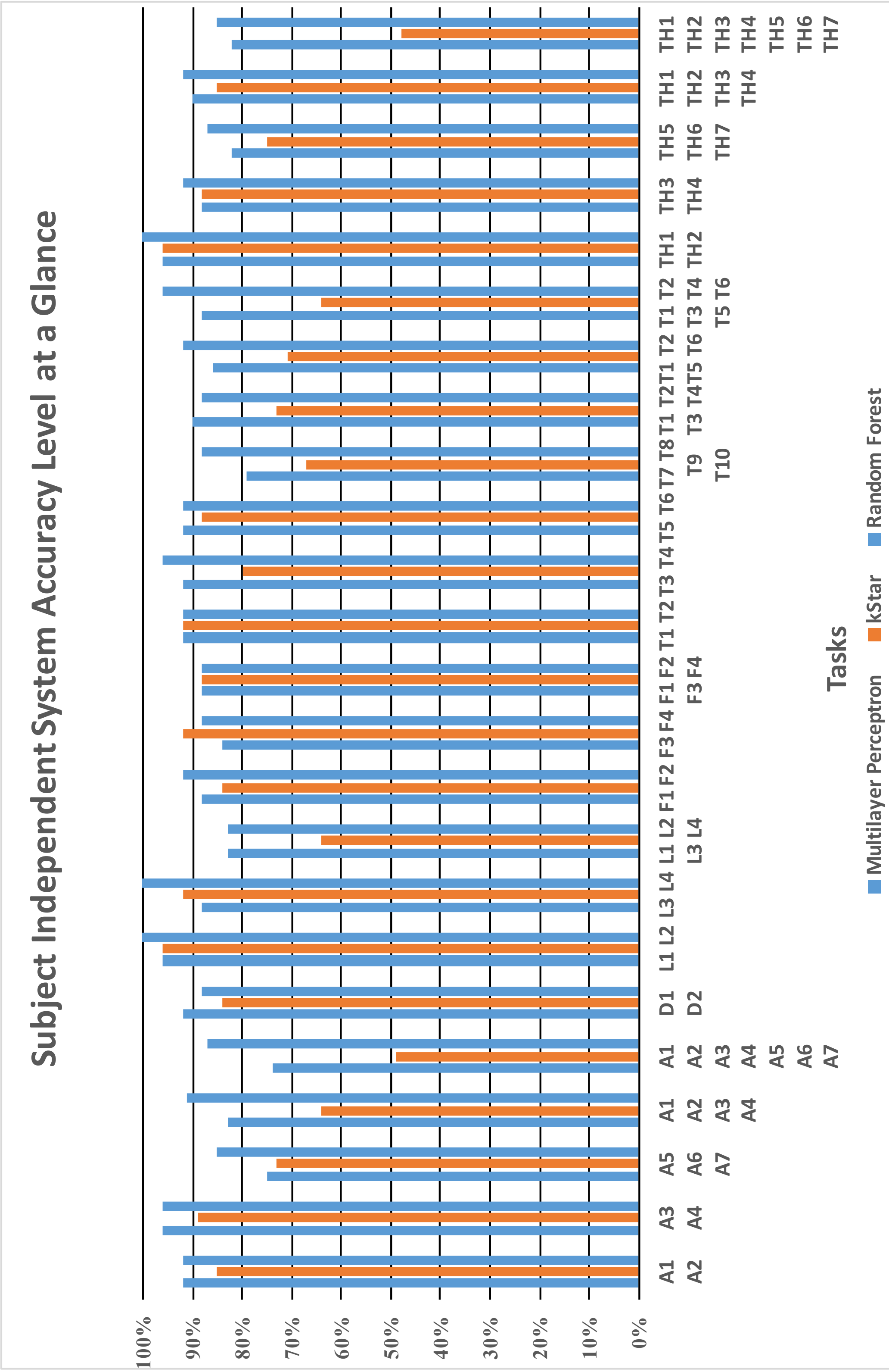


Figure 8.51: Classification results of all the tasks in the Subject-Independent study at a glance.

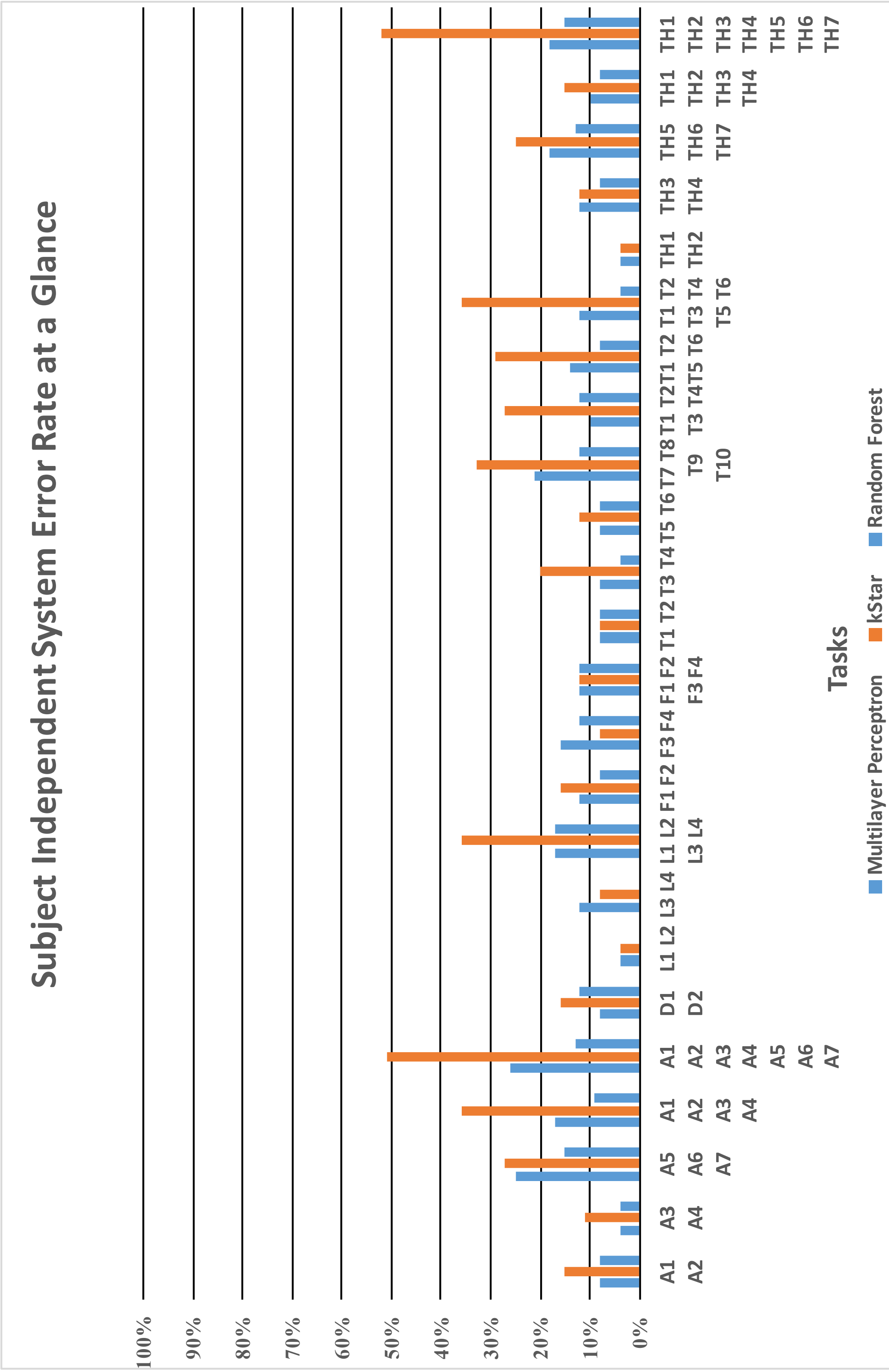


Figure 8.52: Error rates of all the tasks in the Subject-Independent study at a glance.

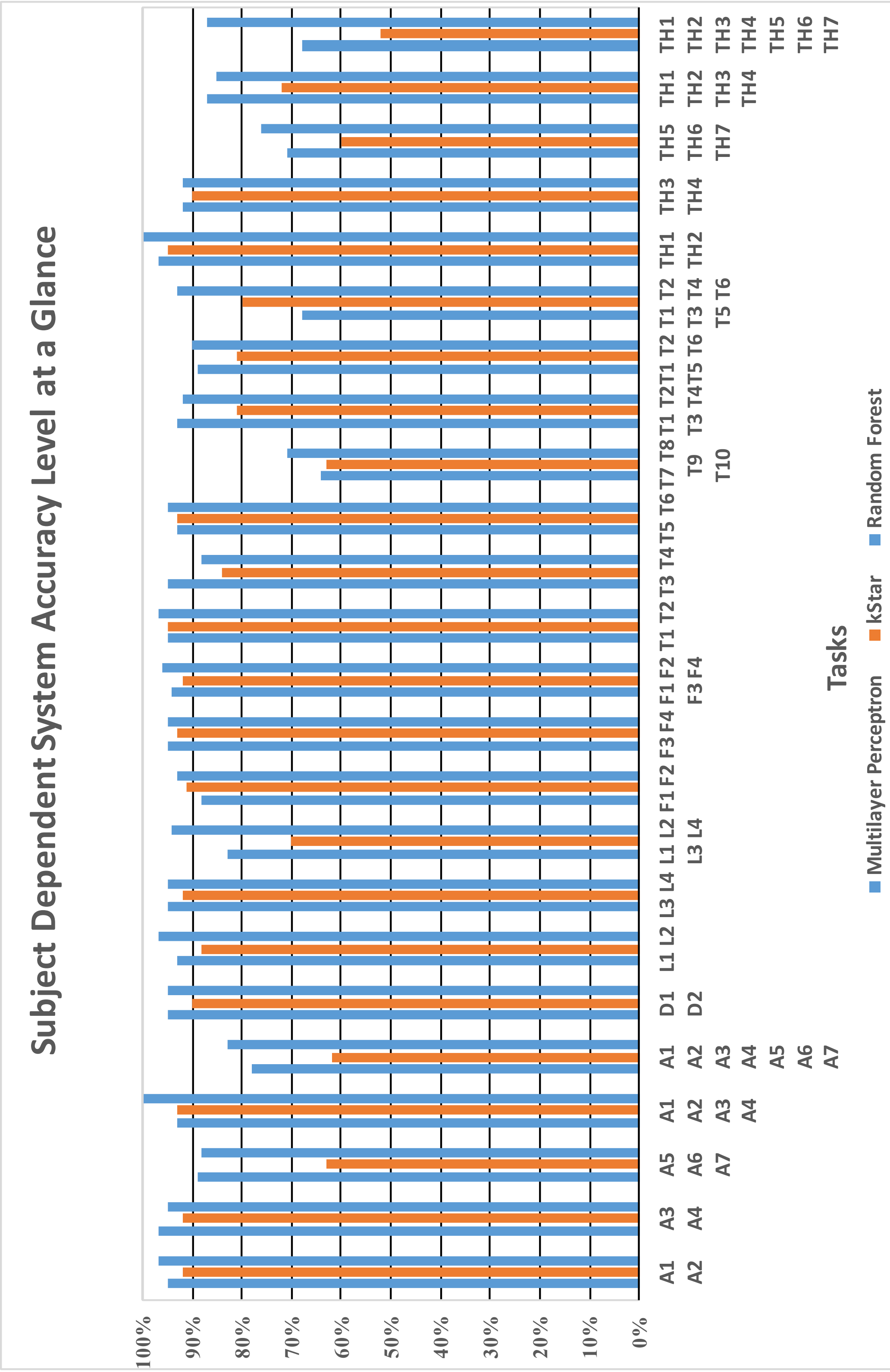


Figure 8.53: Classification results of all the tasks in the Subject-Dependent study at a glance.

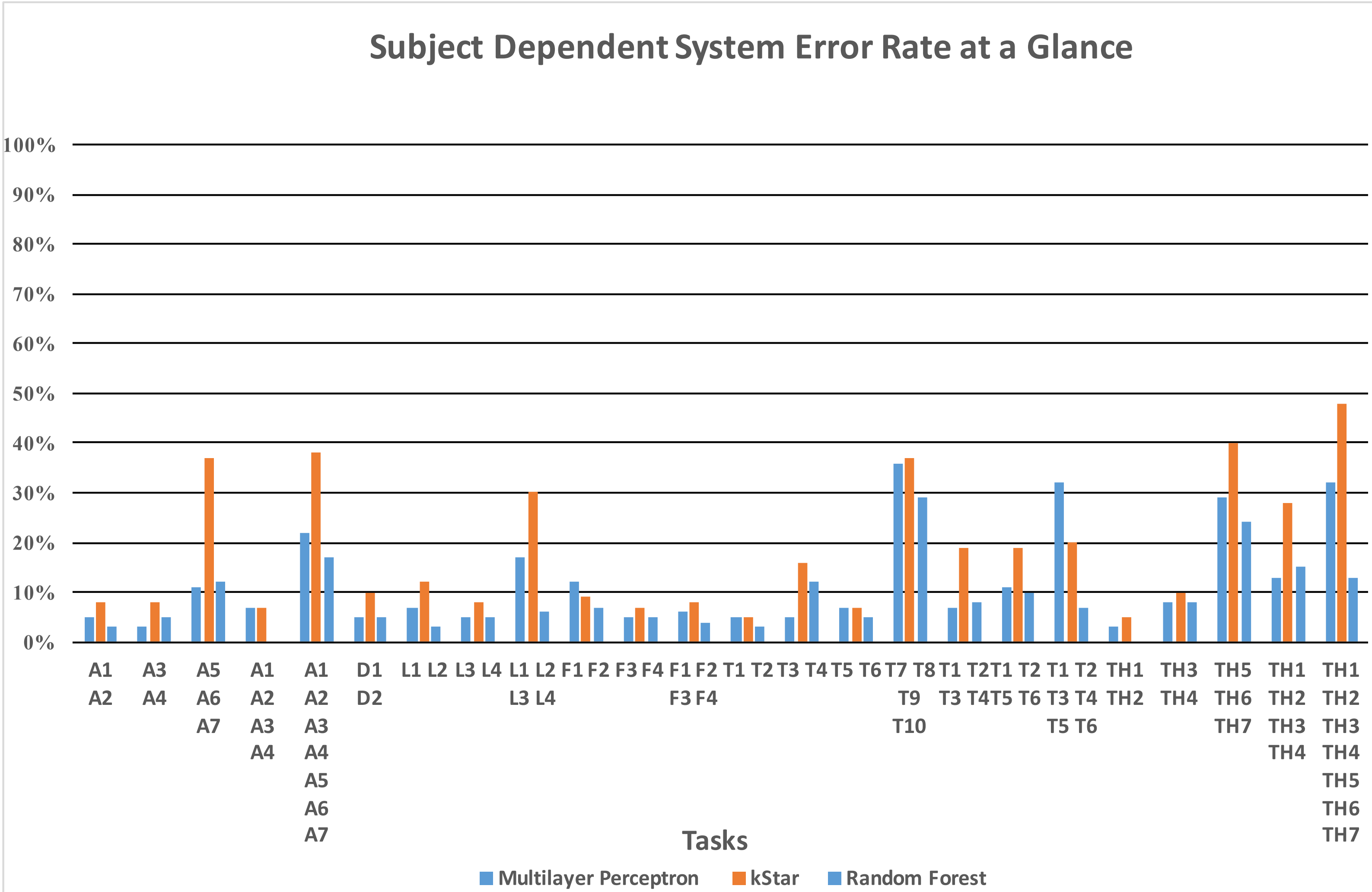


Figure 8.54: Error rates of all the tasks in the Subject-Dependent study at a glance.

Chapter 9

Summary and Future Work

9.1 Summary and Contributions

This thesis investigated thought as a modality to control a smart home environment. In order to do so, we inquired the generalizability of thoughts acquired against various tasks to interact with everyday devices in a smart home environment using both Subject-Independent and Subject-Dependent BCI.

We investigated thought as a modality to control a smart home environment.

We conducted a comparative study to investigate how different people perceived thought as a modality as compared to different means to interact with a smart home environment. These different means to interact with a smart home environment included interacting manually, using voice commands, using gestural commands, using a touch device and using thoughts to convey commands. The participants were explained a scenario regarding each modality and then asked to rate each modality on a 7-point scale on the basis of mental, physical, temporal demand, required effort and preference. According to the gathered results, thoughts were the most preferred modality to control a smart home environment. Although it had the most mental demand, it had the least physical and temporal demand.

A comparative study was conducted to investigate how different people perceived thought as a modality in comparison with other means to control a smart home environment.

According to the subjects, using thoughts to interact with a smart home environment required the least amount of effort.

We investigated the **thought process** behind an action, the **time taken** to think and the **repetitiveness** of a thought to control an everyday device in a preliminary study.

Moving forward, a preliminary study was conducted to investigate the uniqueness of neuro-signals acquired against the thoughts to interact with an everyday device such as a light. This study addressed the research questions regarding the thought process behind an action, the time taken to think about a given task and the repetitiveness of thoughts to control an everyday device. The uniqueness of thoughts was analysed both individually and among different users as well. The results of the preliminary study showed that the subjects imagined the exact steps they planned to perform to do any given task. The average time taken to think about a task to interact with a light was calculated to be 3 seconds. When repeatedly thinking about a particular action to control a light, people thought the same every time. As for the uniqueness of thoughts among different subjects, we classified the recorded neural signals acquired from 30 participants for 4 tasks of turning on/off a given/imaginary light. The recorded signals of all the tasks were classified using 4 different classifiers i.e. kStar, Random Forest, Multilayer Perceptron and Bayesian Logistic Regression with 66%, 80% and 90% percentage split between training and testing data. The highest level of accuracy achieved was 83.3% using Random Forest. As a result of the preliminary user study, it was established that the recorded signals are, in fact, not unique. They are classifiable but to a level a bit higher than chance level in most cases. It was also observed that the classifiablity of tasks to interact with a device e.g. a light, is not effected by the fact that the user was provided with a specific light to think about or was asked to imagine any light.

The average time taken by a person to think about a certain action related to controlling a light is 3 seconds.

The preliminary study provided the evidence that thoughts to control a light are not unique.

Subject-Independent study used neuro-signals acquired from 30 participants against 34 different tasks to control 6 everyday devices to investigate their classifiability.

After the preliminary study, a Subject-Independent study was designed with an extended scope of 6 devices i.e. light, fan, air conditioner, thermostat, television and a door. We introduced black curtains to the study design and noise cancelation headphones to minimize external distractions. The instructions of the study were pre-recorded to ensure consistency during the entire course of the user study. 30 participants were interviewed to record their neural signals for 34 different tasks regarding the previously mentioned 6 everyday devices. Each interview had 3 iterations. As per the gathered qualitative feedback, it was deduced that the simple and concrete tasks such as turning a specific device on or off, turning a specific value such as volume, channel or temperature up or down were relatively easier to imagine for subjects. The classification results also supported these claims by providing the highest level of accuracy for these tasks. It was also reported that tasks with vague terms such as cool, moderate, warm for temperature or switching to a specific TV channel by name, were hard to imagine for users. In general, Random Forest obtained the highest and kStar provided the least level of accuracy for approximately 85% of the time.

Tasks such as turning a specific device on or off, turning a specific value such as volume, channel or temperature up or down were relatively easier to imagine for subjects.

In contrast to the Subject-Independent study, we conducted a Subject-Dependent study with exactly the same setup and study design. The purpose of this study was to present a contrast between BCI trained for one subject as opposed to 30 different subjects. The neuro-signals of one subject were recorded against the same 34 tasks. The interview had 20 iterations. The results were not very different from the ones attained by the Subject-Independent study. The qualitative feedback and the classification results were in line with the results of the Subject-Independent study.

Subject-Dependent study provided the classifiability of signals for a system, trained by one subject, to control a smart home environment.

The results of the Subject-Independent and Subject-Dependent studies established the foundation for the investigation of the level of accuracy a BCI would achieve when controlling a smart home environment.

9.2 Future work

This research proposed a system that uses thought as a modality to interact with a smart home environment. Investigating generalizability of thoughts was just the first step towards creating that system. There are a few other steps that play an important role into creating a BCI system to control a smart home environment. For example, the signal screening process. Currently, the signal screening process had to be performed manually. The subjects had to be

Automating the signal screening process could make the classifier training process faster.

monitored and the neural signal recordings had to be disregarded if they satisfied the exclusion criteria (cf. Section 4.6 – Signal Exclusion Criteria). The manual screening of neural signals made the process of training the classifier of the BCI system quite slow. The possible next step could be to automate the signal screening process. The signal screening process can be automated in such a way that enables the BCI system to detect whether the recorded signals satisfy the criteria of exclusion or not. In case the recorded signals satisfy the exclusion criteria, they will be automatically disregarded. If not, then the acquired signals can be used to train the BCI classifier.

A Home Cloud can be used as processing hub to offload signal processing and classification load.

In totality, we observed that using brain signals as an input to control a device, is a tedious task and it requires quite a lot of processing. For instance, let us consider a user who is given a pre-trained BCI system using which he can interact with a smart home environment. In order to ensure this interaction, there is a lot of internal processing involved. From acquiring his neural signals, screening, pre-processing and classifying his neural signals to actually, performing the corresponding task. A possible extension of the work presented in this thesis can be to have a BCI system with a Home Cloud that can be used as a middleman between the BCI headset and the smart devices. It can be used as a processing hub as proposed by Simoens et al. [2014].

The ultimate goal of this research is to create a BCI to control a smart home environment. This thesis investigated the accuracy level of such a system for both Subject-Independent and Subject-Dependent BCI. Another possible extension could be to investigate the accuracy level of this system for more tasks related to interacting with more everyday devices in a smart home environment. Finally, once a working prototype is developed, the next step would be to analyse this system from the perspective of usability.

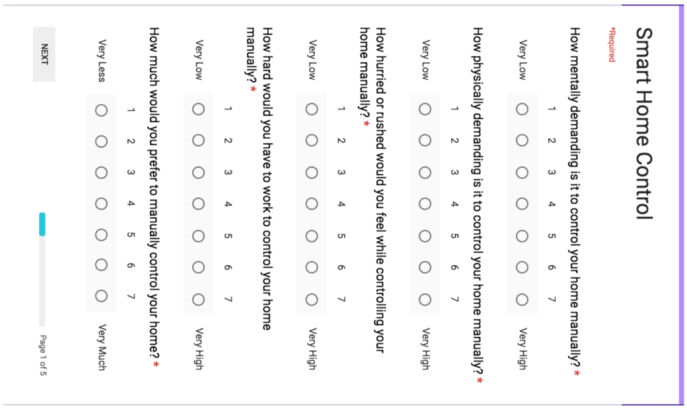
Appendix A

Appendix for the Modality Comparison for Smart Home Control Study

Appendix A includes the questionnaire the participants were asked to fill out to compare and contrast different modalities for the smart home control study.

A.1 Questionnaire

The questionnaire contained 5 sections. Each section belonged to a different modality. In total, the questionnaire had 25 questions, 5 for each modality.



Smart Home Control

*Required

How mentally demanding is it to control your home manually? *

Very Low 1 2 3 4 5 6 7 Very High

How physically demanding is it to control your home manually? *

Very Low 1 2 3 4 5 6 7 Very High

How hurried or rushed would you feel while controlling your home manually? *

Very Low 1 2 3 4 5 6 7 Very High

How hard would you have to work to control your home manually? *

Very Low 1 2 3 4 5 6 7 Very High

How much would you prefer to manually control your home? *

Very Less 1 2 3 4 5 6 7 Very Much

NEXT

Page 1 of 5

Smart Home Control

*Required

Voice Controlled Home

How mentally demanding is it to control your home using voice commands? *

Very Low 1 2 3 4 5 6 7 Very High

How physically demanding is it to control your home using voice commands? *

Very Low 1 2 3 4 5 6 7 Very High

How hurried or rushed would you feel while controlling your home using voice commands? *

Very Low 1 2 3 4 5 6 7 Very High

How hard would you have to work to control your home using voice commands? *

Very Low 1 2 3 4 5 6 7 Very High

How much would you prefer to control your home using voice commands? *

Very Less 1 2 3 4 5 6 7 Very Much

BACK NEXT

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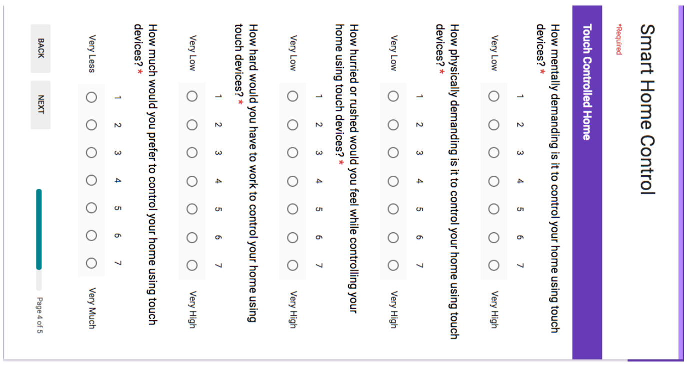

Smart Home Control

*Required

Touch Controlled Home

How mentally demanding is it to control your home using touch devices? *

Very Low 1 2 3 4 5 6 7 Very High

How physically demanding is it to control your home using touch devices? *

Very Low 1 2 3 4 5 6 7 Very High

How hurried or rushed would you feel while controlling your home using touch devices? *

Very Low 1 2 3 4 5 6 7 Very High

How hard would you have to work to control your home using touch devices? *

Very Low 1 2 3 4 5 6 7 Very High

How much would you prefer to control your home using touch devices? *

Very Less 1 2 3 4 5 6 7 Very Much

BACK NEXT

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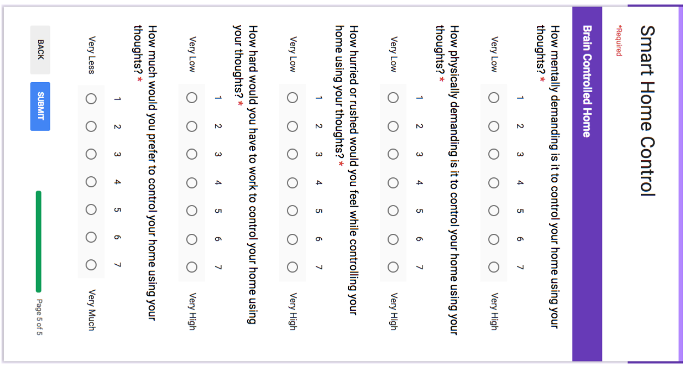
Figure A.1: Modality Comparison for Smart Home Control Questionnaire, pages 1,2,3.



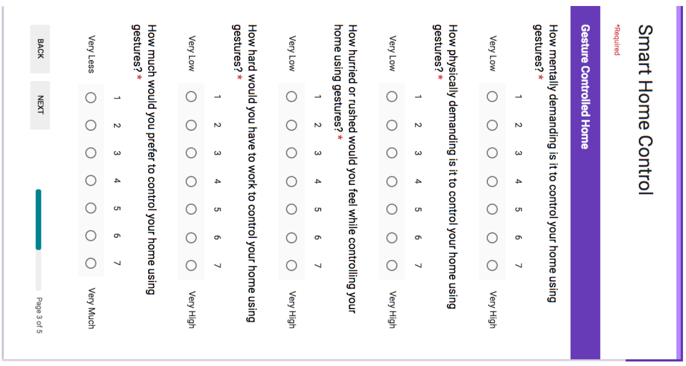


Figure A.2: Modality Comparison for Smart Home Control Questionnaire, pages 4,5.

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