

5-2018

Simplification of EEG Signal Extraction, Processing, and Classification Using a Consumer-Grade Headset to Facilitate Student Engagement in BCI Research

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SIMPLIFICATION OF EEG SIGNAL EXTRACTION, PROCESSING, AND
CLASSIFICATION USING A CONSUMER-GRADE HEADSET TO
FACILITATE STUDENT ENGAGEMENT IN BCI RESEARCH

A Thesis

by

JESUS D. RODRIGUEZ

Submitted to the Graduate College of
The University of Texas Rio Grande Valley
In partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2018

Major Subject: Computer Science

SIMPLIFICATION OF EEG SIGNAL EXTRACTION, PROCESSING, AND
CLASSIFICATION USING A CONSUMER-GRADE HEADSET TO
FACILITATE STUDENT ENGAGEMENT IN BCI RESEARCH

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May 2018

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ABSTRACT

Rodriguez, Jesus D., Simplification of EEG Signal Extraction, Processing, and Classification using a Consumer-Grade Headset to Facilitate Student Engagement in BCI Research. Master of Science (MS), May, 2018, 26 pp., 2 tables, 13 figures, 41 references, 33 titles.

Brain-computer interfaces (BCIs) are an emerging technology that leverage neurophysiological signals as input to computing systems. By circumventing the reliance on traditional input methods (e.g., mouse and keyboard), BCIs show a promising alternative interaction modality for people with disabilities. Advances in BCI research have further inspired a range of novel applications, such as the use of neurophysiological signals as passive input (e.g., to detect and reduce operator workload when managing multiple machines). BCIs have also emerged as a tool for student engagement due to the intrinsic interdisciplinarity of the technology, which spans the fields of computer science, electrical engineering, neuroscience, psychology and their broad applicability. However, these benefits also stand as a challenge to students interested in BCI research, as the need for familiarity with multiple related disciplines creates a high barrier to entry. Towards overcoming this barrier, we developed a simplified EEG-based BCI wherein we integrated a low-cost, consumer-grade headset for signal extraction with a novel graphical user interface that affords seamless exploration of several signal processing and machine learning techniques for analysis. Here, electrical activity is measured in real-time via an extracortical electrode placed on the user's forehead, superior to the prefrontal cortex. The headset can then be connected to any Bluetooth-compatible device via a Bluetooth connection for (1) processing and classification of the signal contents and (2) operation of a machine (e.g., the Cozmo robot) via the intentional brain activity of the user. An additional visualization model also allows the user to explore the signal processing techniques, including the information decomposition and classification.

DEDICATION

To God, my parents, Anadelia and Jose, my siblings, Jose and Ana and every single one of my friends who have continuously supported me throughout my undergraduate, graduate studies and life decisions.

ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. Megan K. Strait, for the immense support, advice and knowledge I received from her and the Social Systems Lab throughout my graduate studies and to my committee members — Drs. Andres Figueroa, Dongchul Kim, and Andrew Winslow — for offering their time and expertise to provide guidance throughout the preparation and finalization of this document. I would also like to extend a special acknowledgement to Virginia Contreras and Ana C. Sanchez from the Social Systems Lab for assisting with data recording of test data samples, which were an essential part of this thesis.

TABLE OF CONTENTS

	Page
ABSTRACT	iii
DEDICATION	iv
ACKNOWLEDGMENTS	v
TABLE OF CONTENTS	vi
LIST OF TABLES	viii
LIST OF FIGURES	ix
CHAPTER I. INTRODUCTION	1
1.1 Background	1
1.2 Contributions	1
CHAPTER II. BRAIN-COMPUTER INTERFACES (BCI) AND EEG TECHNOLOGY ...	2
2.1 Extraction of Brain Data: From Invasive to Non-invasive Techniques	2
2.1.1 Invasive	2
2.1.2 Partially-invasive	3
2.1.3 Non-invasive	4
2.2 In Depth: EEG-based BCIs	5
2.2.1 Band Powers	5
CHAPTER III. DATA ACQUISITION & ANALYSIS	8
3.1 EEG Headset	8
3.2 Extraction	8
3.3 Signal Processing	10
3.4 Classification	10
CHAPTER IV. EEG-BASED BCI SYSTEM	11
4.1 System Overview	11
4.2 System Implementation	12
4.2.1 Main Window	12
4.2.2 Task Setup and Classification Window	14
4.3 System Application Integration	15

4.3.1	Cozmo Robot Simulation via PyGame	16
4.3.2	Physical Cozmo Robot via CozmoSDK	16
4.4	Preliminary Evaluation	18
CHAPTER V. DISCUSSION		20
5.1	Limitations and Avenues For Future Work	20
CHAPTER VI. CONCLUSION		22
BIBLIOGRAPHY		23
BIOGRAPHICAL SKETCH		26

LIST OF TABLES

	Page
Table 4.1: Results of 5-fold cross-validation of the three-class classification (baseline versus blink versus tapping), including the overall mean (M) and standard deviation (SD) by subject.	18
Table 4.2: Results of 5-fold cross-validation of the five-class classification (baseline, forward, backward, left, and right), including the overall mean (M) and standard deviation (SD) by subject.	18

LIST OF FIGURES

	Page
Figure 2.1: Invasive and non-invasive methods for Brain-Machine Interfaces (BMI).	3
Figure 2.2: Band Powers.	6
Figure 3.1: Brain-Computer Interface System Process Flow.	9
Figure 3.2: Raw EEG Data of a blink sample.	9
Figure 3.3: Bandpass filtering, convolving and window filtering of a single blink sample. . .	10
Figure 3.4: Signal filtering using an estimation of Power Spectral Density and Frequency Response of blink sample.	10
Figure 4.1: EEG MindSet's electrode placed on forehead.	11
Figure 4.2: Screenshot of the BCI System's Main Window.	12
Figure 4.3: Screenshot of Task Setup and Classification Window.	14
Figure 4.4: Screenshot of the Cozmo Simulator.	16
Figure 4.5: Picture of the Cozmo Robot, being controlled through mental task.	17
Figure 4.6: Cozmo-Interaction Classification State Controller.	17
Figure 5.1: Revised Cozmo-Interaction Classification State Controller.	21

CHAPTER I

INTRODUCTION

1.1 Background

Brain-computer interfaces (BCIs) leverage neurophysiological signals as input to computing systems. By circumventing traditional input methods (e.g., mouse and keyboard), BCIs hold great promise as an alternative interaction model for people with physical disabilities. Advances in BCI research have further inspired a range of novel applications, such as the use of BCI as passive input (e.g., to detect and reduce operator workload in complex tasks). Due to the intrinsic interdisciplinarity of BCIs (which spans the fields of computer science, electrical engineering, neuroscience, and psychology), BCIs can also be used as a method for broad student engagement in research. However, this interdisciplinarity also poses a challenge to engagement, as the need for familiarity with each related discipline creates a high barrier to entry.

1.2 Contributions

Towards overcoming this knowledge barrier found within BCI research, we developed a simplified EEG-based BCI system integrating a low-cost, consumer-grade headset for signal extraction with a novel graphical user interface for exploring signal processing and machine learning techniques for analysis. Additionally, we integrated the system with both a simulated and physically-embodied robotic platform — Cozmo — to demonstrate direct control of an application via intentional brain activity.

CHAPTER II

BRAIN-COMPUTER INTERFACES (BCI) AND EEG TECHNOLOGY

BCI technologies have gained traction in both academic and public fields as the technology advancements surrounding the development of BCI devices have approached a more consumer-targeted market [1]. In particular, the ability of BCI technologies to serve as an alternative input method (e.g., to mouse/keyboard) fills a critical gap in communication technologies for people with disabilities [29]. For example, BCIs have emerged for people with locked-in syndrome (LIS) and amyotrophic lateral sclerosis (ALS) — disabilities that interfere with movement, speech, and other forms of communication — to provide alternative means of communicating based on neurophysiological signals to circumvent traditional input methods. BCI systems capable of performing communication via gaze, for LIS and ALS patients have emerged in [4] and [33], helping throughout the development of systems capable of aiding patients with disabilities to communicate by allowing a neurofeedback-based touchless interaction with a device.

2.1 Extraction of Brain Data: From Invasive to Non-invasive Techniques

Brain signals can be extracted via a number of mechanisms, which range from highly invasive (e.g., cortical implants) to non-invasive (e.g., sensors placed external to and atop the head via a wearable device); see 2.1.

2.1.1 Invasive

Invasive BCI technologies involve the direct contact with cortical matter through implantation of electrodes directly into the brain. Such BCIs provide maximal spatial resolution, with the ability to localize measurements down to single neurons. Due to this degree of spatial specificity, invasive techniques have enabled partial function restoration such as mobility and vision

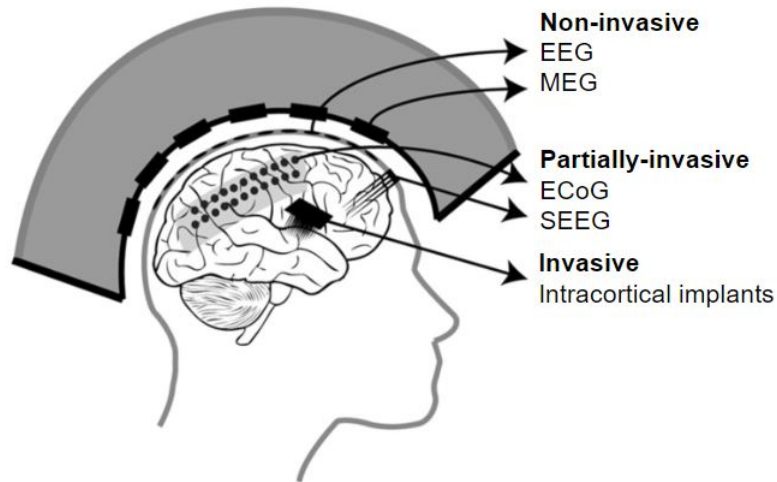


Figure 2.1: Invasive and non-invasive methods for Brain-Machine Interfaces (BMI) (modified from reference [3]).

to individuals with paralysis and vision impairments [2]. Invasive techniques work by the measurement of either action potentials (e.g., [16]) or of local field potentials (e.g., [27]). Action potentials are measured from single or few neurons, which emit a summative electrical signal when enervated. Local field potentials reflect the electrical activity of a population of neurons. Both methods (sampling of action potentials and local field potentials) require implantation of intracortical sensors.

2.1.2 Partially-invasive

Similar to invasive techniques, partially-invasive approaches require surgical implantation beneath the skull. However, unlike invasive techniques, partially-invasive systems only require implants in the *dura* mater — an extracortical layer that surrounds the brain [2]. Two examples of partially-invasive systems include electrocorticography (ECoG) and stereoelectroencephalography (SEEG).

Electrocorticography (ECoG) ECoGs are composed of thin plastic pads called, micro and macrogrids. They allow for a more complex understanding of cognitive, motor and language tasks by taking advantage of a more invasive approach to retrieving brain wave signals [21]. The technique is partial invasive because of the possibility of scar tissue damage on implantation.

Stereoelectroencephalography (SEEG) SEEGs are partially invasive techniques that can cover extensive areas of the head with high accurate sampling using direct implantation through the scalp into the *dura* mater of the brain. They are a form of therapeutic application alternative for deep-seated lesions (e.g., patients with epilepsy) [9].

2.1.3 Non-invasive

Non-invasive techniques are those that do not involve direct contact with brain matter or the outer layer of brain.

Functional Near-infrared spectroscopy (fNIRS) This non-invasive techniques is used through optical imaging. It enforces the idea that safety is a priority and as explained in the fMRI, the functional component allows in real-time measure of brain activity. This is achieved by measuring the changes in oxygen levels of the blood in the brain, which is linked to changes in neural activity that accompanies changes in the blood flow [24].

Functional Magnetic Resonance Imaging (fMRI) This technique involves the usage of MRI imaging to collect scanning of sectors in the brain that represent visual cues and motivational processes such as hunger [22], where by approaching the data retrieval from a perspective point of a scan can allow for higher-degree of flexibility within the process of signal acquisition and the patient.

Magnetoencephalography (MEG) MEG is a non-invasive technique used with the intent to record neuronal activity of the brain through a processes of measuring magnetic fields created by the brain. It is known that the technology provides signals with higher spatioemporal resolution greater than EEG techniques [13].

Electroencephalography (EEG) While the non-invasive EEG technique tends to yield a lower performance against other BCI retrieval techniques [30], they offer a safer approach for brain-signal acquisition by using electrodes placed on specific areas of the head scalp without the need for direct contact with the brain. The accessibility of recording accurate data with this technology requires the use of gel-covered electrodes, however, the thought of applying gel or

wet electrodes on every use tend to create an issue, as it becomes rather time consuming and difficult to use. For this, EEG headsets using dry electrodes, have also been targeted.

2.2 In Depth: EEG-based BCIs

It wasn't until Hans Berger made the discovery of brain activity based on mental activity with the use of EEG techniques that initiated the development of more complex brain activity recorders [11]. EEG has become widely more used as dry electrodes have now emerged as the possible form of consumer product that will allow individual users the simple requirement of putting on the device [32]. This intriguing technology allows the field of multi-purpose research development surrounding BCI.

Applications surrounding the use of this technology have surfaced with the idea of using easy to use BCI devices to control computer applications such as the one proposed in [28], consisting of a BCI device with a neurofeedback computer game that uses the EEG Emotiv EPOC+ headset with an implemented acquisition module for signal processing. This module allows the measurement and recording of brain signal coming from the electrodes, where they will then be processed through signal filtering and fed into a classifier model for action classification with the intention to interact with a connected machine.

This BCI advancements have made it possible for some patients to have partial control of doing simple daily life tasks such as communicating, controlling computer interfaces and prosthetic limbs with the use of their brain [15]. With that perspective, researchers and developers can now use readily available EEG headsets to explore on their own the possibilities and limitations of the technology without the requirement of specialized and expensive medical tools.

2.2.1 Band Powers

In EEG, the band powers, or also known as EEG Band Frequencies, are referred to the bands defined by their frequency of waves (e.g., Delta, Theta, Alpha, Beta, and Gamma) shown in Figure 2.2. Each of these bands frequency are dependent to different mental state activity. The following information regarding band powers and their brainwave state was defined in [6], and

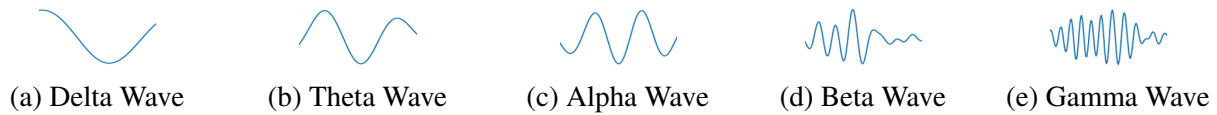


Figure 2.2: Band Powers.

recompiled by [17, 14].

Delta Delta waves, or slow wave activity as shown in Figure 2.2a; range from 0.5 to 4 Hz. They are the slowest brainwaves and are associated within the function of a deep state of sleep or dreamless sleep during non-rapid eye movement sleep [5]. Having too much could mean that there are brain injuries, learning problems if situated within a deep-sleep state. While having too little, could then indicate that there exists an inability to revitalize the brain, body and can lead to poor sleep pattern [14].

Theta Theta waves, as shown in Figure 2.2b; are more associated with daydreaming and sleep. They tend to range from 4 to 8 Hz, and can be considered to be more active during strong internal focus and meditation. This state consists of being in its optimal state during the process of creativity, emotional connection, intuition and relaxation. Too much theta brain activity could mean depression, hyperactivity, inattentiveness, such as ADHD. However, if too little is found, then its regarded as poor emotional awareness, stress or anxiety [14].

Alpha Alpha waves, as shown in Figure 2.2c; sometimes are divided into two sections, low and high as they tend to range from 8 to 12 Hz, and belong in the moderate frequency. The low activity in this waves are associated with relaxation and disengagement, and high activity can be regarded as too relaxed, and could be categorized as daydreaming effects. Relaxant intake can help in the increase of alpha waves [14].

Beta Beta waves, as shown in Figure 2.2d; and just like Alpha waves, are divided into two sections, low and high. The range from this wave can go from 12 to 30 Hz, and are part of the high frequency range. The low state (12-18 Hz) are associated while being in a conscious focus, problem solving, active thinking and concentration, while the high waves (18-30 Hz) can be associated with alertness and agitation (e.g., in a panic state). An abnormal amount of beta

waves can lead to experience stress or anxiety. In order to increase beta waves activity have been linked to coffee, energy drinks and other stimulant intake [14].

Gamma Gamma is the fastest of the brain activity waves as shown in Figure 2.2e; and can range from 30 to 70 Hz. They are involved in cognitive processing and information insight. Optimal gamma waves are more prominent to learning and mental activity (e.g., good memory and efficient problem solving can be associated to gamma wave activity occurring at 40 Hz). They are associated with learning, reading and speaking. An abnormal high amount of gamma activity could indicate anxiety, high arousal, and stress. However, a very low amount of gamma activity could be classified as ADHD, depression and learning disabilities. A way to increase good gamma brain activity can be linked to meditation [14].

CHAPTER III

DATA ACQUISITION & ANALYSIS

In this chapter, the processes of data extraction and analysis will be covered in detail to further cover the techniques used in our proposed BCI system. The proposed system process flow diagram is shown in Figure 3.1.

3.1 EEG Headset

In our system setup, we use the NeuroSky EEG MindSet headset as our brain wave signal retriever. The headset comes with a single dry electrode attached to the device that is placed at the left frontal lobe area of the forehead when in use as pictured in Figure 3.1 within the EEG Signal acquisition state. The underlying of how the data was retrieved through the Bluetooth connection and manipulated from the headset was described in an explicit manner in the provider's product documentation website, NeuroSky Inc [18].

3.2 Extraction

In the EEG signal acquisition process, EEG data is sampled from the user's prefrontal cortex via the EEG MindSet headset Bluetooth communication ports. Even though the MindSet headset provides pre-filtered data by default, it is only accessible as a single data point once every second using covert methods for brain signal processing. In our system, the data is retrieved as raw data at 512 samples per second or once every 2 milliseconds, this give us the flexibility to fully understand the data being recorded to later processes and analyze using signal filters and classification methods. Figure 3.2 shows the raw EEG data of a single blinking wave being sampled.

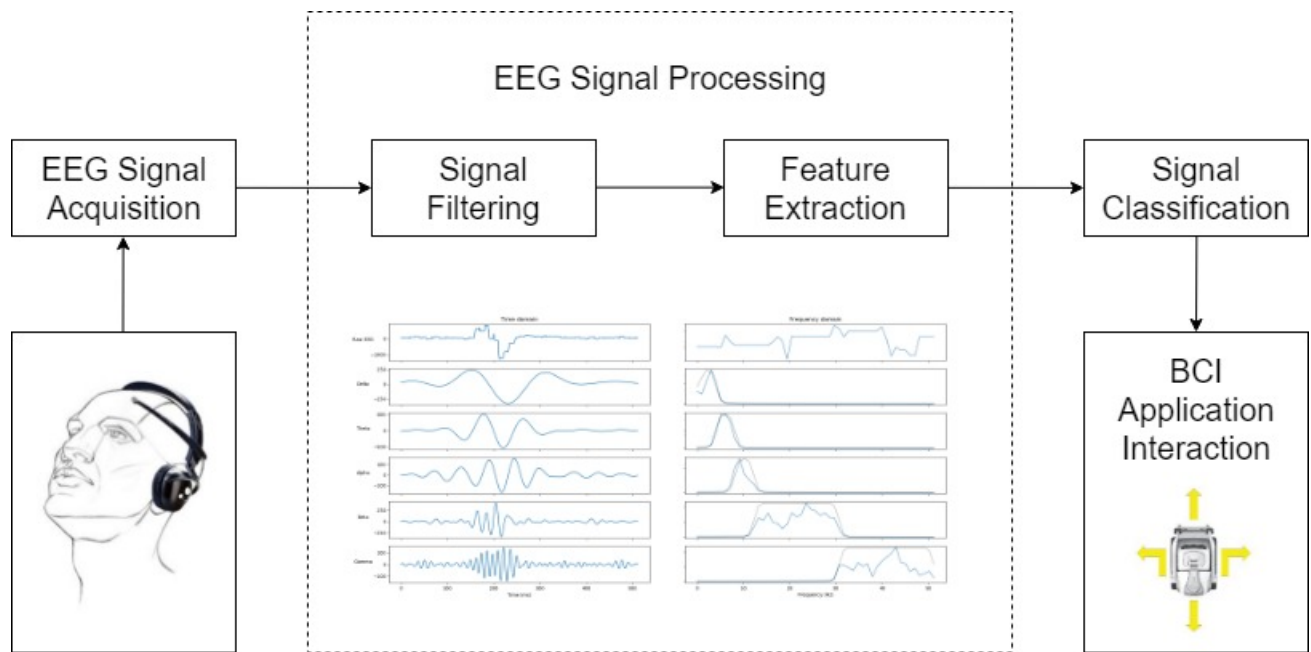


Figure 3.1: Brain-Computer Interface System Process Flow.

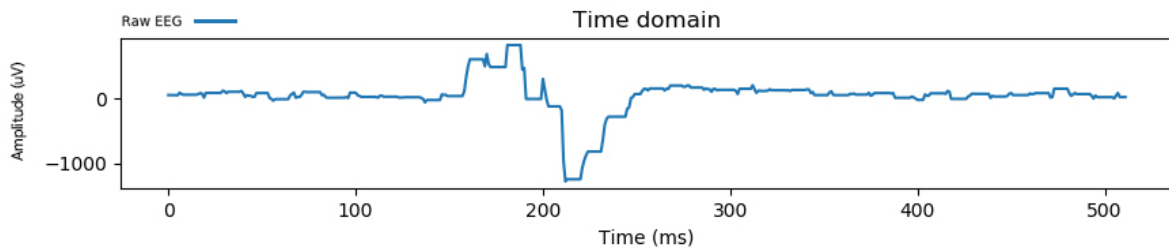


Figure 3.2: Raw EEG Data of a blink sample.

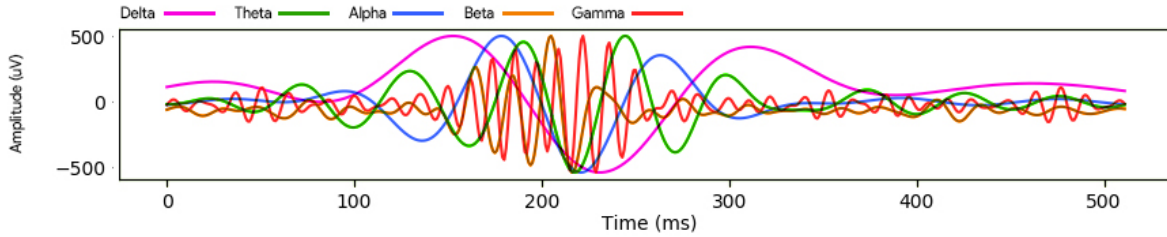


Figure 3.3: Bandpass filtering, convolving and window filtering of a single blink sample.

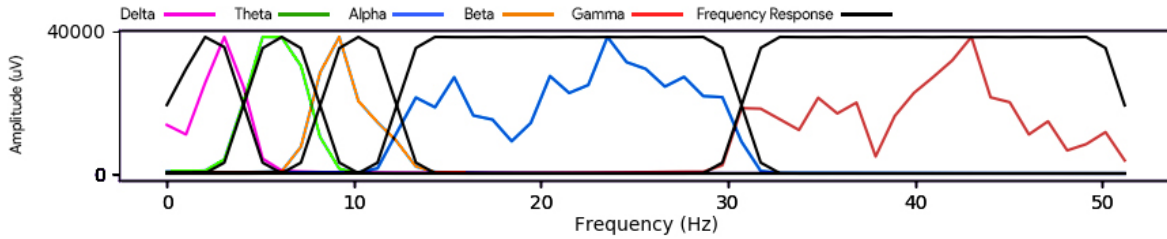


Figure 3.4: Signal filtering using an estimation of Power Spectral Density and Frequency Response of blink sample.

3.3 Signal Processing

Inside the signal processing module, a raw data sample will require three rigorous signal manipulation steps. (1) Bandpass filtering through Filter Impulse Response (FIR), convolving and window filtering as shown in Figure 3.3. (2) The estimation of Power Spectral Density (PSD) using the squared magnitude of the Fast Fourier Transform (FFT) on each band power wave [31]. (3) And performing a Frequency Response (FR) on filtered band power waves from frequency domain [26] allowing the splitting of band powers into their respective band bins composed of Delta, Theta, Alpha, Beta and Gamma waves as shown in Figure 3.4.

3.4 Classification

At the end of the post-processing filtering, the signal features from the separated bands are then used as input to a hierarchical multiclass support vector machine (SVM) model [8] that will allow the quickness of building and training models based on the tasks selected.

CHAPTER IV

EEG-BASED BCI SYSTEM

This chapter will cover an overview of the system design, its implementation and testing scenarios.

4.1 System Overview

The proposed EEG-based system to overcome the knowledge barrier between interdisciplinary research towards BCI applications was developed with the purpose of being used with low cost, consumer-grade headsets for signal acquisition, as those created by NeuroSky Inc. (e.g., MindSet, MindWave and MindWave Mobile) and inspired by the work of [12].

With the task of setting up a ready-to-use system for interdisciplinary research, we decided to write the project in its entirety in Python, as it is considered to be an easy to read and understand high-programming language for non computer science students and researchers, as opposed to other high-level programming languages [7] while also allowing us to develop the required components for the system.



Figure 4.1: EEG MindSet's electrode placed on forehead (modified from reference [23]).

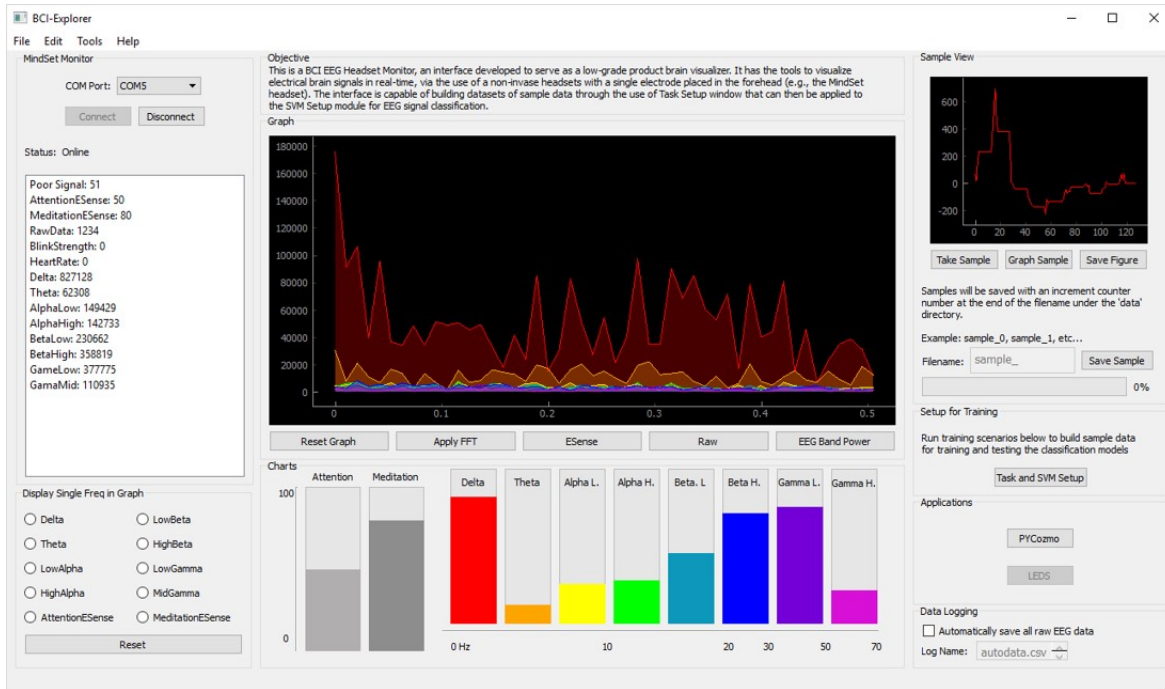


Figure 4.2: Screenshot of the BCI System’s Main Window.

In our system setup, we use the NeuroSky EEG MindSet headset. The headset comes with a single dry electrode attached to the device that is placed at the left frontal lobe area of the forehead when in use as shown in Figure 4.1. In order to interact with the headset through the application, we decided to create a parser that would break any information going through the communication port and translate it into useful data. Any underlying of the process behind parsing Bluetooth connection from the headset was described in explicit manner and followed from the provider’s product documentation website [18].

4.2 System Implementation

The proposed BCI system was built with two screen windows; (1) a main system window screen and (2) the task setup and classification window screen.

4.2.1 Main Window

As shown in Figure 4.2, the main window screen contains five important modules to notice. A detail explanation of how each of the modules operate will be described next.

Headset-Bluetooth Connection. The Bluetooth Connection module is based on the technology that is available in the headset and computer as a form of communication protocol. The component allows the selection of any available communication ports (e.g., windows based: 'COM0, COM1 ... COMN' and UNIX based 'refcomm0, ... refcommN', where N represents any given number).

By pressing the connect button, the program will then attempt to make a connection with the headset through the specified port. If successful, the status label and program state will switch from "Offline" to "Online" and then activate the process of retrieving data from the headset. However, if the connection is found not successful, it will then re-attempt to connect with the headset until a timeout of 20 attempts is reached. If no connection is made, the program throws an error message inside the status label describing the issue (e.g., "Error no device found.", "Error the port is busy at this moment.", etc.).

Brain Signal Visualizations. The Graphing and Power Bars visualization modules allow for the students to interact and explore the decomposition of raw signal waves in real-time into its respective band powers. It can also be used as a visualization tool to observe the default signal recording from the headset and filtered classifications (e.g., the eSense Attention and Meditation meters) and its intensity to each other brain wave.

Sample Testing Module. The Sample View module in the main screen focus on the simple idea of both visualizing the filtered brain data and the availability to take a snapshot of a specific brain-signal segment by simply pressing the "Take Sample" button. The snapshot will be recorded in a time interval specified by the given input time number in milliseconds. The data will be represented by 1 data point recorded each 2 milliseconds. This module also contains the feature of graphing, saving the sample and figure created of the current snapshot taken; allowing for a greater understanding of the raw and filtered band power data retrieved from the snapshot of data collected.



Figure 4.3: Screenshot of Task Setup and Classification Window.

Task Setup and Classification Module. This encompasses the button available for clicking under this module. The functionalities of the window that launches after clicking the button will be described in the next section in detail to focus this section on those components that can be interacted solely within the main window screen.

Application interaction Module. This module contains buttons that when pressed, they will launch an application. Applications linked to the buttons are in itself simply normal application that can be interacted with a keyboard and a mouse. However, a minimal application modification allows the addition of an special module behind the program that will allow the usage of the EEG headset for direct interaction through a machine learning classifier.

4.2.2 Task Setup and Classification Window

As shown in Figure 4.3, the 'Task Setup and Classification Window' is composed of several modules. Three of them are very specific and important to note; below we give a concise and detailed definition of these modules.

Task setup and data collection. Within the Task Setup module, the system allows the creation of multiple task scenarios to record. The idea within this module is that it will create a modular way of constructing one's own task scenarios without having to code a single line. By pressing the 'Tools' option at the top of the current application window, will display a simple task-creation window with the specifications required to create a custom-task scenario. Once the task is created, the task setup section of the module will allow the recording of subject-labeled samples for the new selected task and save it directly into its corresponding subsequent directories (e.g., taskname->subjectname->samplerecording.csv).

Datasets and SVM Training/Testing The module simplifies the collecting and combining of data samples into complex datasets. It offers its users the power to group and select multiple files from a file explorer window, where each selected sample file will then be combined into the final dataset as a matrix. To train and test the model, we took advantage of the Python library *sklearn* [19] to create a predefined classification model that can be initialized within the SVM Setup window. We used the following parameters to define our SVM classification model: $C = 1$ for our penalty parameter of the error term, a linear kernel and a random state for shuffling samples. The rest of the options were left as is, since they had no impact on our linear kernel. The classification model will then divide the data into a training and testing set for training the model. After the model has finished training, the system will then automatically create and store a persistent copy of the training SVM model. Any new created data recordings can be used and tested against this machine learning model for accuracy evaluation within the same window.

4.3 System Application Integration

To test our trained models on a interactive application we implemented two applications for testing, (1) a Cozmo Robot Simulation via PyGame and (2) the physical Cozmo robot via CozmoSDK.



Figure 4.4: Screenshot of the Cozmo Simulator.

4.3.1 Cozmo Robot Simulation via PyGame

The implemented simulation of the Cozmo robot platform was built using the Python game engine framework, Pygame [20] as shown in Figure 4.4 with the purpose of allowing research students the availability to interact with the simulator as if they were using the physical robot. We developed a top down view that represented the physical robot core movements (e.g., moving forward, moving backwards, turning left and turning right.) and at the same time we integrated our classification model for testing into the game through an SVM classification persistent-trained model to classify mental tasks in real-time to control the Cozmo robot movement inside the simulator.

4.3.2 Physical Cozmo Robot via CozmoSDK

The physical Cozmo robot interaction was developed using the Cozmo SDK, provided by Cozmo developers, Anki [10]. The core movements were controlled through a Python script that was activated by the classified input from the EEG headset, as seen in 4.5.

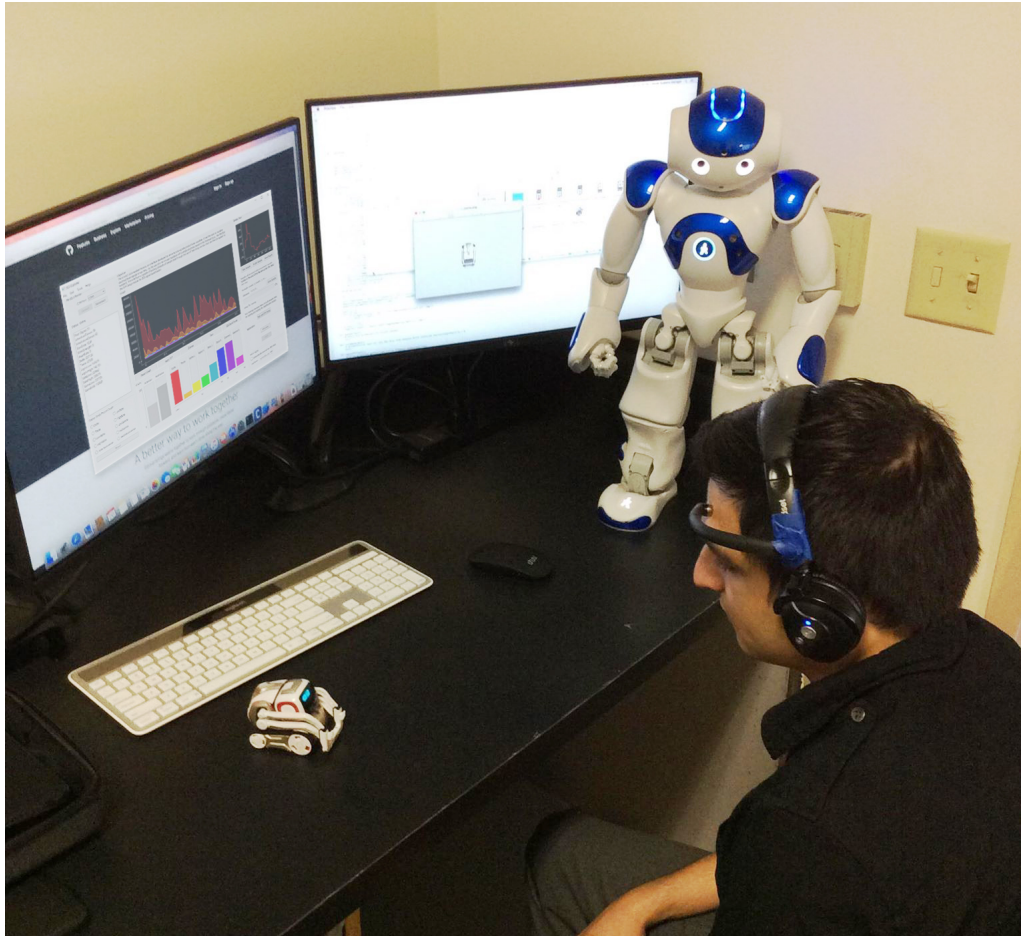


Figure 4.5: Picture of the Cozmo Robot, being controlled through mental task.

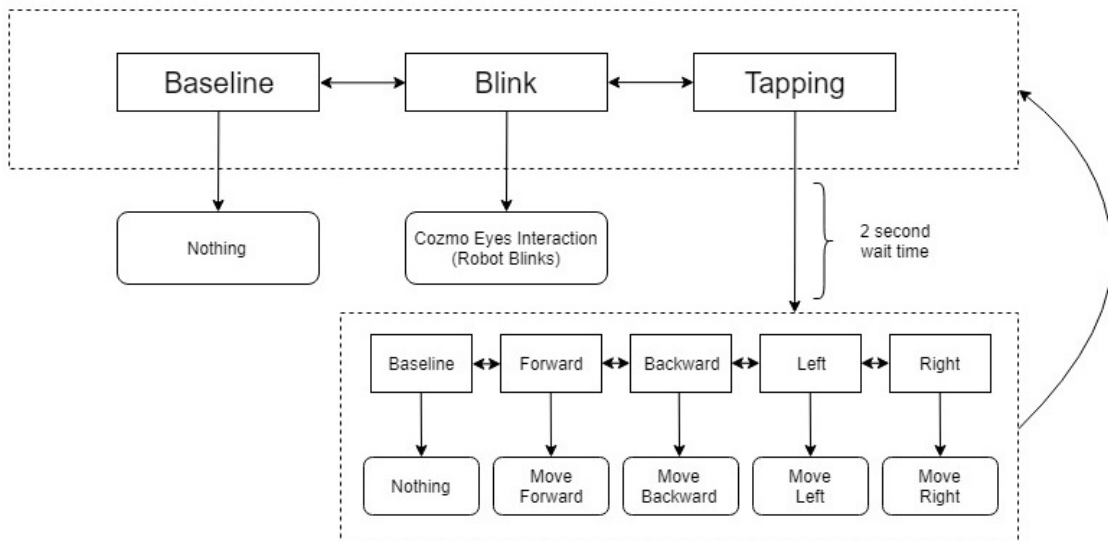


Figure 4.6: Cozmo-Interaction Classification State Controller.

Table 4.1: Results of 5-fold cross-validation of the three-class classification (baseline versus blink versus tapping), including the overall mean (M) and standard deviation (SD) by subject.

	F1	F2	F3	F4	F5	M	SD
S1	80.0%	80.0%	86.6%	80.0%	80.0%	81.3%	2.6%
S2	64.7%	86.6%	73.3%	78.5%	78.5%	76.3%	7.2%
S3	80.6%	86.6%	73.3%	73.3%	73.3%	77.3%	5.3%

Table 4.2: Results of 5-fold cross-validation of the five-class classification (baseline, forward, backward, left, and right), including the overall mean (M) and standard deviation (SD) by subject.

	F1	F2	F3	F4	F5	M	SD
S1	25.9%	42.3%	46.1%	33.3%	31.8%	35.9%	7.3%
S2	22.2%	53.8%	46.1%	37.5%	50.0%	41.9%	11.2%
S3	29.6%	38.4%	46.1%	50.0%	36.3%	40.1%	7.2%

4.4 Preliminary Evaluation

To verify our system implementation, we conducted a preliminary evaluation using data from three volunteer participants. For each participant, we collected 200 samples of each class of activity (baseline, blink, tapping, forward, backward, left, and right) using our Task Setup and Data Collection GUI module.

We first verified the SVM’s ability to detect noise (blinking) in two-way classification (discrimination of blinking from baseline activity). ”Baseline” is assumed to correspond to low prefrontal activity; whereas blinking is expected to be readily distinguishable due to the spiking of EEG signals that it introduces. 5-fold cross-validation on the 200 samples per class per participant showed an overall accuracy of 90.6% (SD=5.03%).

Next, we conducted 5-fold cross-validation on our three-way and five-way classifications found within our Cozmo-interaction state controller (as seen on 4.6). The three-way classification was composed of baseline, blinking, and tapping signal data. ”Tapping” corresponds to intentional tapping was done to the headset by the subject. Once tapping is confirmed, it will open the next classification state under tapping after a delay of 2 seconds, allowing for a 5-way classification: Baseline vs Forward vs Backward vs Left vs Right, after the completion of the classification

it will then return to the first state. This test resulted with a mean accuracy of 78.3% (SD=2.65%) as shown in Table 4.1.

Lastly, we conducted 5-fold cross-validation on the five-way classification of baseline, moving forward, moving backwards, turning left and turning right signal data that corresponded to control movements. The four movement tasks pertain to brain activity related to their physical action (e.g., thinking of moving or turning towards a given direction). After the completion of the second state classification, it will loop back to the first state, where it will initiate the three-way classification again. The initial results from this classification were low with a mean accuracy of 39% (SD=3.07%) as shown in Table 4.2. However, both accuracies were found to be well above chance considering 33% represents guessing at three-way classification and 20% for five-way.

CHAPTER V

DISCUSSION

Towards overcoming a knowledge barrier intrinsic to BCI research, we developed a simplified EEG-based system by integrating a low-cost headset, novel GUI, and accessible robot platform for signal extraction, evaluation, and application. At the same time our classification model implementation used on our state controller showed a good performance in three-way detection of action instantiation ($M=78.3\%$, $SD=2.65\%$ for Baseline vs Blinking vs Tapping) and in a five-way detection of control movements ($M=39\%$, $SD=3.07\%$ for Baseline vs Forward vs Backward vs Left vs Right).

5.1 Limitations and Avenues For Future Work

After processing our initial evaluation of our Cozmo-integration classification state controller, we noted a very important usability feature that should be included within the current design of the controller regarding exiting and entering the second state and a way to continuously classify repeated actions under that state without the additional requirement of creating an intentional headset tap. We then decided to revise the state controller in its entirety to properly address the limitations of our current design and implement the new controller. Figure 5.1 shows the revised Cozmo-integration classification state controller and its composed of four states; (1) perform a 3-way classification as the previous version of the controller (Baseline vs Blink vs Tapping). (2) If intentional headset tapping classification is detected on the first state; it will then jump to the second state mapped in color red. Inside the red state, it will only jump to either the blue or green state based on a 4-way classification (Forward vs Backward vs Left vs Right). If either the Forward or Backward task classification is activated, then it will jump to the third state.

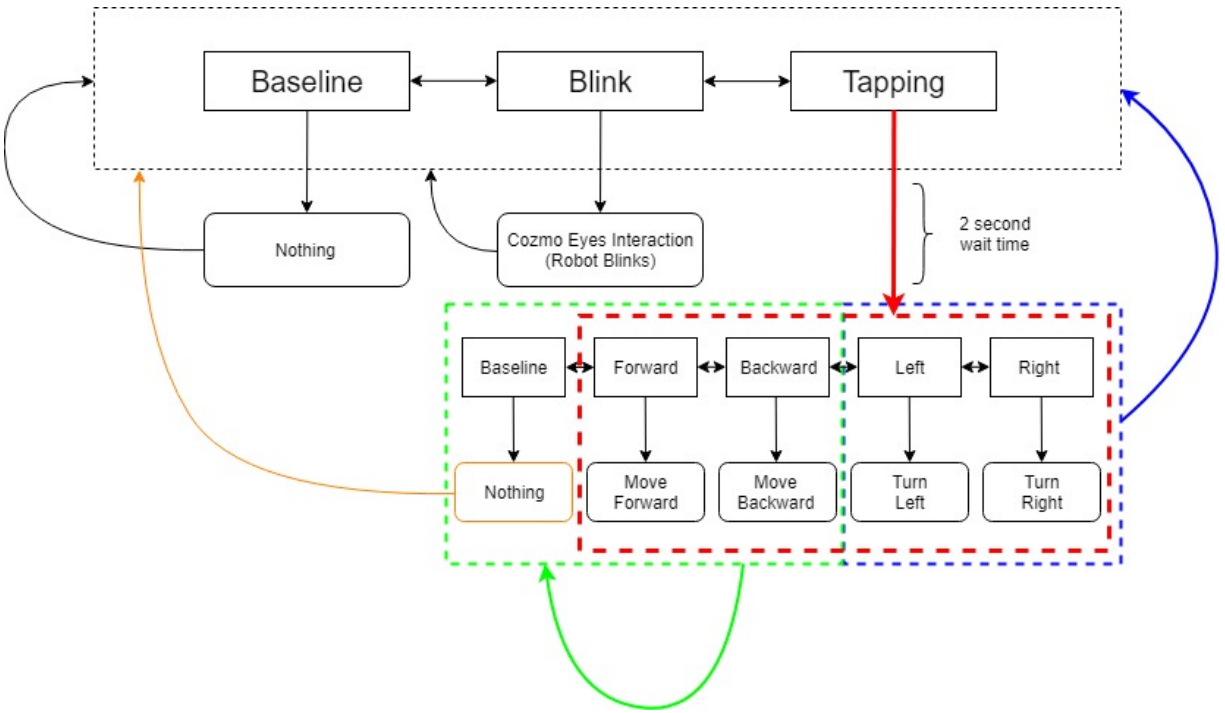


Figure 5.1: Revised Cozmo-Interaction Classification State Controller.

(3) Within the third state (green), any actions will only then be based in a 3-way classification (Baseline vs Forward vs Backward); if either the Forward or Backward actions are classified from the three, then it will keep on checking for further intentional classifications within the green color state in a continuous loop. However, if Baseline (yellow) is classified inside the green state; then it will exit the current state and return to the first state. (4) Now, if the classification ends in either the Left or Right task classifications from the red state, it will then exit that current state (blue) and return to the first state. This revisions to the controller were made to allow a more seamlessly and continuous interaction with the Cozmo robot while still being in control of the movements.

CHAPTER VI

CONCLUSION

We developed a system which simplifies the procedure of connecting a EEG headset, acquiring data, performing signal processing and visualization. In addition, we were able to integrate a classifier and a Cozmo-interaction application to test signals produced within the system. The system and classification implementation shows a good performance (averages of 90.6% for two-way, 78.3% for three-way and above chance of 39% in a 5-way classification) in our preliminary evaluations with possible room for improvements.

Next we aim to further expand the system features to include additional EEG headset support (e.g., Epoc+ developed by Emotiv and the Ultracortex "Mark IV" EEG Headset developed by OpenBCI) and implement more applications for testing (e.g., Raspberry Pi integration to toggle other small systems ON and OFF, smart LED light bulb deemng) allowing direct control of electronics by applying mental task classification based on certain brain states. At the same time, we plan to implement more complex models of cognition (e.g., a neural network with logistic regression [25]) for classification to assess other approaches and their accuracy in interpreting EEG data for direct control systems.

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BIOGRAPHICAL SKETCH

Jesus D. Rodriguez was born in Monterrey, Nuevo Leon, Mexico and moved to Hidalgo, Texas, USA in 2005. After the completion of his schoolwork at Valley View High School in 2011, Jesus entered the University of Texas Rio Grande Valley in Edinburg, Texas. He received a Bachelor of Science in Computer Science in December 2016. The following semester he decided to continue his education and pursue a higher degree. In January 2017, he entered the graduate program for Master of Science in Computer Science at the University of Texas Rio Grande Valley in Edinburg, Texas. While attending the graduate program, he found a passion for doing work that involved research studies. In spring 2017, he joined the Machine Learning Laboratory to research automation and classification of radar imagery based on a Synthetic Aperture Radar (SAR) simulator. In the summer of 2017, he joined the Social Systems Lab with a focus on researching Brain-Computer Interfaces under the supervision of Dr. Megan K. Strait, founder of the Social Systems Lab and Computer Science professor. He decided to use the knowledge learned throughout the research towards his graduate thesis, later earning him a Master of Science in Computer Science from the University of Texas Rio Grande Valley in May 2018; after successfully defending his thesis. If you would like to know more about his work; the best way to reach him is through his personal email address at: jesus.d.rodriguez01@gmail.com.